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A Resource-Allocation Perspective for Marketing Analytics

Your friend has sent you on a treasure hunt. She has given you clues about how to find the treasure, but you'll be left to draw on your own treasure-hunting skills to put the clues to good use.

Who is this friend of yours? It's your boss, the owner of the company for which you are the marketing manager. What is the treasure you seek? It's a business advantage that will allow your company to allocate its marketing dollars optimally and come out ahead of the competition. Those clues? That's data your company has gathered about the past behavior of customers. And what are your treasure-hunting skills? They are the tools you will find in this note—the techniques needed to analyze past marketing performance and discover unknowns that will allow you to predict the future.

The broad view of how this is done is the discipline of marketing analytics—the process of creating models helpful in understanding consumer behaviors. It is the systematic use of empirical data about customers, companies, their competition and collaborators, and industry context to inform strategic marketing decisions. The function of marketing analytics can range from reports on regular marketing activities—such as paid search advertising click-through rates—to allocating marketing resources to maximize future performance of a company's digital presence.

You have a lot to learn, and there's no time to waste. You've got treasure to find.

Why Marketing Analytics?

Companies are placing high value on customer data these days. As technology has allowed firms to link customer behaviors more closely with the drivers behind those behaviors, more and more companies are becoming comfortable using marketing analytics to gain a business advantage.

A 2013 report in *Forbes* magazine covered a survey of 211 senior marketers that showed that most large companies have had success using big data to understand customer behaviors. More than half (60%) of organizations that used big data a majority of the time reportedly exceeded their goals, whereas companies that used such data only occasionally reported significantly less success. Almost three-quarters of companies that used big data a majority of the time were able to understand the effects of multichannel campaigns, and 70% of that group of companies said they were able to target their marketing efforts optimally.

Consider the effect of advertising. In the past, when television and print advertisements were the predominant form of pushing a firm's message, the relationship between ads and customers' willingness to purchase the item advertised was not entirely clear. The firm rarely knew whether customers bought the item

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because they had seen a television advertisement or because they had heard about it through some other channel. Collecting data about the success of the advertisements was indeed difficult.

With the advent of email and web-based advertising, all that has changed. Firms are now able to closely connect their inputs (e.g., ad placements) and outputs (e.g., whether the target of the advertisement made a purchase). This produces a large amount of behavioral data. These data, in turn, allow companies to model existing customer behaviors and predict future behaviors more precisely. (It is important, however, to note that with big data comes a big problem—namely, the risk of false positives, or seeing patterns among chance events.[1])

To avoid making mistakes with big data, business intuition is critical. Intuition allows the savvy marketing manager to select the correct inputs and outputs for a model. Analytics allows a company to take this traditional static dashboard of metrics or measurables and turn it into a predictive and dynamic entity.

Marketing analytics is not a new field. It simply allows companies to move beyond reports about what is happening in their businesses—and alerts about what needs to be done in response—to actually understand why something is happening based on regressions, experiments, testing, prediction, and optimization.[2] What is new is how skilled companies have become at using marketing analytics. The availability of granular customer data has transformed firms' marketing-spending decisions. Sophisticated econometrics combined with rich customer and marketing-mix data allow firms to bring science into a field that has traditionally relied on managers' intuition.[3]

The Resource-Allocation Framework

Resource allocation is the endgame of analytics for any company. Using marketing analytics properly, any firm should be able to determine the optimal level of spending it should make on each of its marketing channels to maximize success.

Resource allocation is a four-step process, the first of which is to determine the objective function. What is the metric the company wants to set as its goal for optimization? This may be one of any number of methods of assessing business success, including conversion rates to sales, incremental margins and profits, customer lifetime value (CLV), near-term sales lift, new buyers, repeat sales, market share, retention rates, cross-sell rates, future growth potential, balance sheet equity, and business valuation.

The second step is to connect the marketing inputs of a firm to the objective of resource allocation. Business managers' intuition is of paramount importance in this stage, as it allows the marketer to correctly decompose a metric. For example, if a company is examining gross profits, what are the attributes of the business that contribute to those profits, and are the relationships between the various components empirical or computational (i.e., identity relationships)? **Figure 1** shows one way in which gross profits might be broken down. Sales is a function of price, advertising, sales force, and trade promotions. Because gross profits minus marketing yields net profits, manipulating marketing channels can improve sales, but the different channels are also cost centers.

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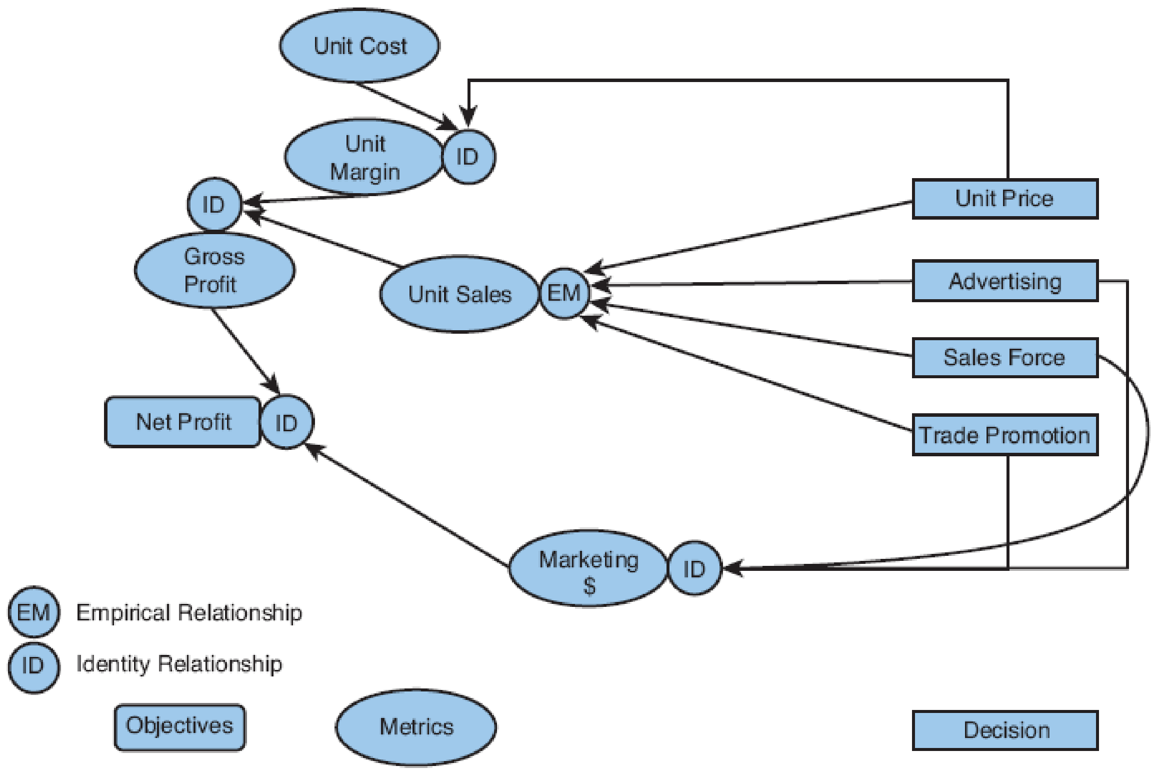
[1] Wes Nichols, "Advertising Analytics 2.0," *Harvard Business Review*, March 2013.
[2] Thomas Davenport, *Competing on Analytics: The New Science of Winning* (Boston, MA: Harvard Business School Press, 2007).
[3] Nichols.

Figure 1. A system-of-metrics framework for net profits.



Source: Adapted from Farris, Pfeifer, Bendle, and Reibstein.[4]

Once the marketing inputs are mapped to the objective, as shown in **Figure 1**, the marketing manager must determine which relationships are accounting identities and which are empirical. An accounting identity can be computed without any unknowns. For example, in **Figure 1**, net profit is gross profit minus marketing costs. If both gross profit and marketing costs are known, net profit can be computed easily. On the other hand, the relationship between marketing costs and unit sales is more complex and driven by numerous unknowns. You cannot directly sum the investments in marketing (e.g., price, advertising, sales force, and trade promotion) to obtain sales. The relationship is termed empirical because the manager must analyze historical data to develop a function that transforms the marketing inputs into sales (e.g., describes the relationship between price and sales). The transformation function ideally develops a weight that translates a product's price into sales. These weights do not provide a perfect transformation, but rather a best guess based on historical data, wherein several factors in addition to price also affect sales. This is the main difference between an identity relationship and an empirical relationship: empirical implies a best guess or prediction; identities are certain.

The third step in the resource-allocation process is to estimate the best weights for the empirical relationships identified in the second step. A common method for identifying these weights is to build an

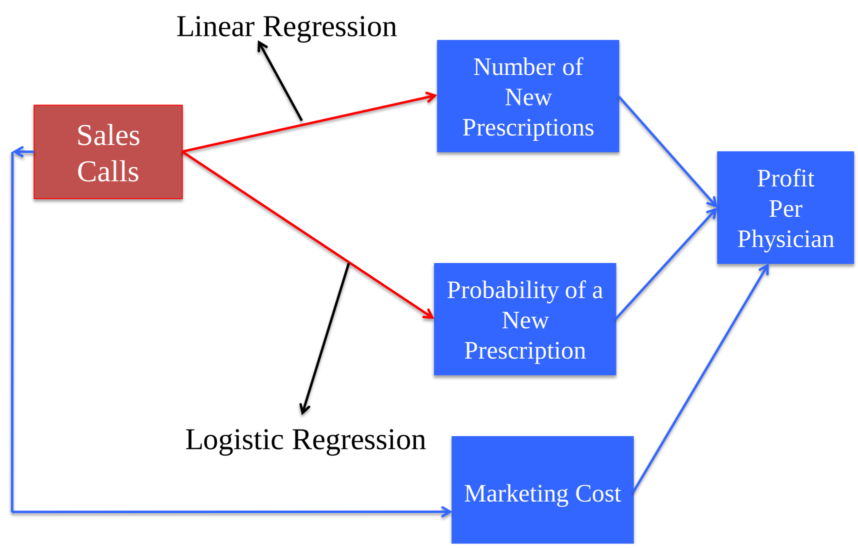
[4] Paul Farris, Phillip Pfeifer, Neil Bendle, and David Reibstein, *Marketing Metrics: The Definitive Guide for Measuring Marketing Performance* (Upper Saddle River, NJ: FT Press, 2010).

econometric (regression) model. Which marketing inputs of interest (e.g., price, advertising, sales calls) should be considered as having an effect on the dependent variable? Once this regression model is obtained, the marketing manager can predict the precise shape of the objective function. This is the mathematical model that describes the relationship between the independent variables (e.g., price, advertising, and sales calls) and the dependent variable (e.g., market share, profits, CLV).

In the last step of the resource-allocation process, a firm can reverse the process to identify the optimal value of the marketing inputs to maximize the objective function. This gives a detailed picture of what the company's precise marketing spend should be on each channel it uses to market its product.

Consider a pharmaceutical company in which the marketing department wants to determine the effects of sales calls on the profits it makes per customer (i.e., physicians are customers). In **Figure 2**, profits are broken down into number of new prescriptions and probability of new prescriptions. Both can be represented as a function of sales calls.

Figure 2. An example of the system of metrics in the pharmaceutical industry.



Source: Unless otherwise noted, all figures created by authors.

Because sales calls also represent a marketing cost, the goal is to balance their effect on the top and bottom lines to maximize profits. The marketing manager can express the relationship between sales calls and profits mathematically and perform both linear and logistic regressions[5] as follows (**Equation 1**):

$$\text{Profit per physician} = \text{new prescriptions} \times \text{prob (new prescriptions)} \times \text{gross margin\%} - \\ \text{\# of sales calls} \times \text{unit cost of sales calls}$$

$$\text{\# of new prescriptions} = a + b1 \times ln(\text{\# of sales calls})$$

$$\text{prob (new prescriptions)} = \exp(u) \div [1 + \exp(u)], \text{ where } u = c + d1 \times ln(\text{\# of sales calls}). \quad (1)$$

[5] See Shea Gibbs and Rajkumar Venkatesan, "Multiple Regression in Marketing-Mix Models," UVA-M-0855 (Charlottesville, VA: Darden Business Publishing, 2013) for a discussion of linear regressions; and Shea Gibbs and Rajkumar Venkatesan, "Logistic Regression," UVA-M-0859 (Charlottesville, VA: Darden Business Publishing, 2013) for more on logstic regression analyses.

Performing the regression analyses will determine the values of *a*, *b*1, *c*, and *d*1, giving the marketing manager a mathematical way to value sales calls with respect to the company's ability to increase the number of prescriptions written by physicians and the probability of a new prescription. And because sales calls are a cost center, the pharmaceutical company can maximize total profits by weighting its number of sales calls subject to optimal spending under its budget limit (**Figure 3**).

Figure 3. Optimal allocation of marketing spend.

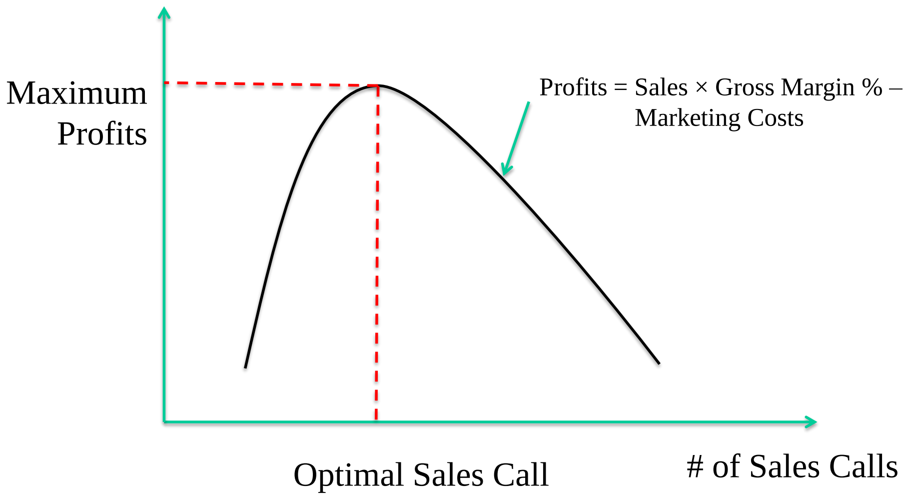


Figure 4 provides hypothetical data describing the effects of sales calls on profits per physician. Say the values for *a*, *b*1, *c*, and *d*1 turn out to be 0.05, 1.5, 0.006, and 1.2 based on our regression analysis.

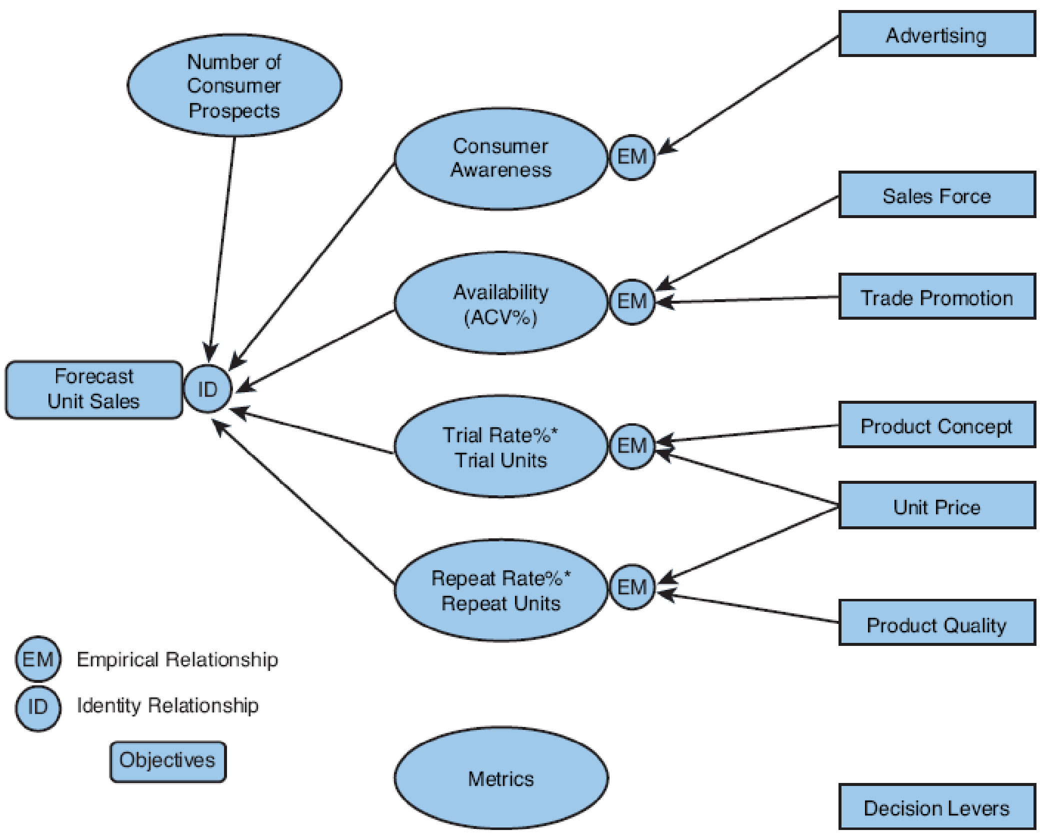
Figure 4. Numeric example of optimal allocation of marketing spend.

a	***b*1**	***c***	***d*1**	**Price**	**Cost of Sales Calls**
0.05	1.5	0.006	1.2	300	50
Sales Calls	**Sales**	***u***	***p*(Sales)**	**Profit**	
1	1.09	0.84	0.70	109.73	
2	1.70	1.32	0.79	181.65	Current
3	2.13	1.67	0.84	226.31	
4	2.46	1.94	0.87	252.30	
5	2.74	2.16	0.90	265.25	
6	2.97	2.34	0.91	268.74	Optimal
7	3.17	2.50	0.92	265.10	
8	3.35	2.64	0.93	255.94	
9	3.50	2.77	0.94	242.39	
10	3.65	2.88	0.95	225.27	

The price of a unit (a prescription drug) is $300, and the cost of a single sales call is $50. The drug company currently calls its physicians an average of twice per month (which means that, in this example, the number of sales calls is two). Based on the estimated weights for each unknown in the described relationships, this strategy yields a profit of $181.65. If the company were to increase sales calls to six per month, the expected profits would be $268.74. Increasing sales calls beyond six per month, however, makes the cost of the sales calls higher than their incremental benefits, meaning profits start declining for sales calls of seven per month and above. In this example, six is the optimal level of sales calls because it maximizes the expected profit ($268.74) from each physician. As the example illustrates, the optimal number of sales calls that maximizes profits is critically dependent on the unknown weights of the empirical relationship.

Figure 5 shows a decomposition commonly used by consumer-goods companies to forecast the performance of new products. Using this model, a company can study how advertising leads to awareness and how the sales force leads to availability, among other things. Once the company understands the empirical relationships mathematically, it can calculate expected sales using simple arithmetic.

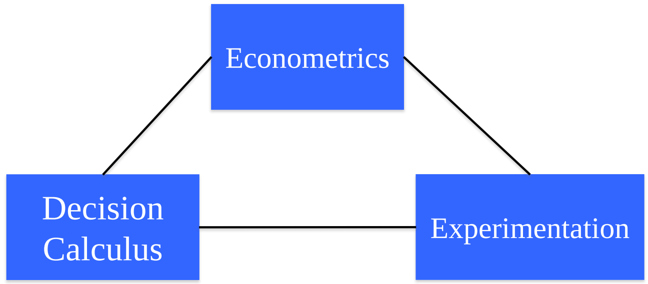
Figure 5. System of metrics to forecast new product sales.



Source: Adapted from Farris, Pfeifer, Bendle, and Reibstein.

Marketing analytics relies on three pillars: econometrics, experimentation, and decision calculus (**Figure 6**).

Figure 6. Three pillars of marketing resource allocation.



Managers can use econometrics when they need to make hypotheses about their business and test them by using experiments. Where the decision calculus comes down to individual companies introducing their own intuition into the equation, marketing analytics as a whole allows firms to identify best estimates for how to weight the effects of marketing activities. Intuitively, these weights should provide the best relationship between marketing inputs and consumer response. Looking at past cases wherein a firm has tried different levels of marketing inputs and observed consumer response reveals this relationship.

Measuring ROI: Did the Resource Allocation Work?

The goal of marketing analytics is to determine the effectiveness of a company's various marketing strategies (i.e., its marketing mix). For each strategy, the company is looking to assess its return on investment (ROI).

Financial ROI is equal to profit over investment value. This is a yearly rate that is comparable to rate of return. Marketing ROI, on the other hand, is equal to profits related to marketing measures divided by the value of the marketing investment—which is actually money risked, not invested (**Equation 2**):

$$\text{Marketing ROI} = \text{Incremental Sales} \times \text{Gross Margin} - \text{Marketing Investment} \div \text{Marketing Investment}. \quad (2)$$

Determining ROI is simple arithmetic; however, estimating and defining the effects of ROI is difficult. Imagine that Powerful Powertools spends \$2 million on search engine marketing in 2012 and generates \$10 million in incremental sales that year with marketing contribution margins of 50%. The company would determine its marketing ROI as follows (**Equation 3**):

$$\text{ROI} = (\$10\text{M} \times 0.5 - \$2\text{M}) \div \$2\text{M} = 1.5. \quad (3)$$

A marketing manager or CFO would have therefore determined that the return is 150% on the marketing investment. But the manager will likely still have questions. Will the investment in 2012 also pay dividends in 2013 (i.e., should some new customer acquisitions in 2013 be attributed to the investment in 2012)? How was incremental gross margin determined? What is the baseline without the search engine marketing? Will doubling the investment to \$4 million double the returns to \$20 million in incremental sales, or are there diminishing returns to marketing? What are the longer-term effects, and what is the CLV of the customers acquired through this campaign? The goal of analytics is to accommodate these nuances of marketing's influence on sales so that the estimate of incremental sales is an accurate reflection of reality.

One major decision regarding marketing ROI concerns the choice of average versus marginal ROI. Average ROI represents the returns for any given level of marketing investment. If an executive is interested in how total returns to marketing spending have changed over the previous two years, average ROI is the right measure. Marginal ROI, on the other hand, is the return for an additional dollar spent on marketing relative to existing investment levels. The choice between marginal and average ROI relies to a large extent on whether a marketing measure may yield diminishing returns. For linear models, average and incremental returns are the same because regardless of the current level of spending, the returns will be identical (**Figure 7**). As shown in **Figure 8**, however, the current level of investment matters when calculating incremental returns in the presence of diminishing returns.

Figure 7. A linear sales response curve.

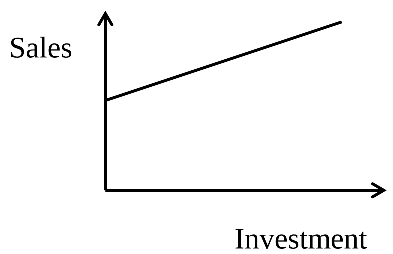
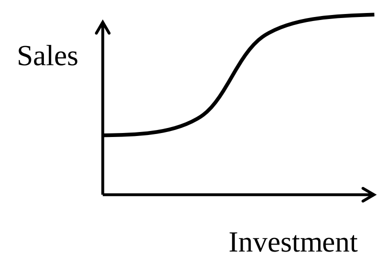


Figure 8. Sales response curve with diminishing returns.



Working with Econometrics: IBM and Others

To improve marketing success, companies must consistently make good decisions about which customers to select for targeting, what level of resources to allocate to the selected customers, and how to nurture the selected customers to increase future profitability. One example of a company that has successfully used CLV as an indicator of customer profitability and allocated marketing resources accordingly is IBM. In 2005, the computer and technology company used CLV as a criterion for determining the level of marketing contacts through direct mail, telesales, email, and catalogs. An overview of the CLV management framework is shown in **Table 1**.

Table 1. Customer lifetime value management framework.

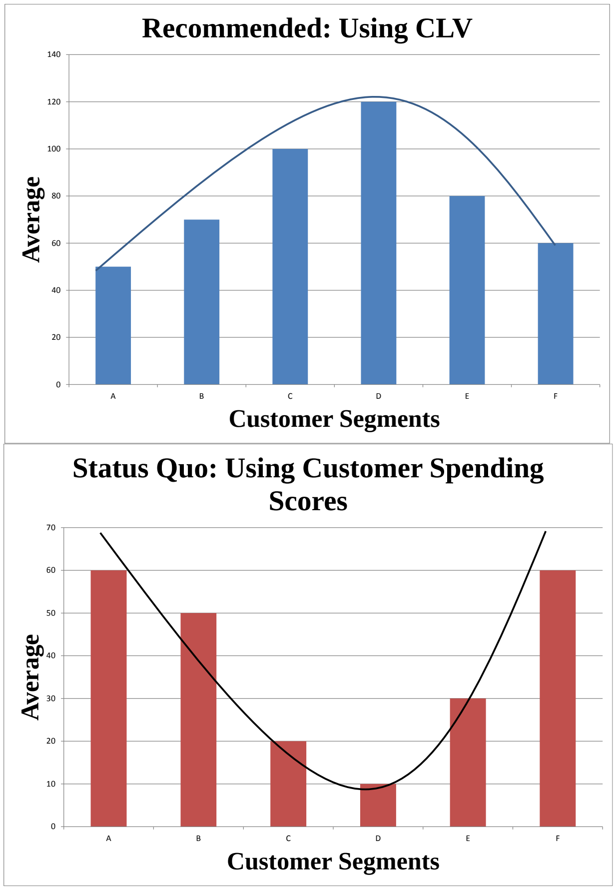
Process	Purpose
Measure CLV	To obtain a measure of the potential value of IBM customers
Identify the drivers of CLV	Allow managers to influence CLV
Determine optimal level of contacts for each customer that would maximize his or her respective CLV	To guide managers about the level of investment required for each customer
Develop propensity models to predict which product(s) a customer is likely to purchase	To develop a product message when contacting a customer
Reallocate marketing contacts from low-CLV customers to high-CLV customers	To maximize marketing productivity

Source: Adapted from Kumar et al. (2005)[6]

[6] V. Kumar, Rajkumar Venkatesan, Tim Bohling, and Dennis Beckmen, "The Power of CLV: Managing Customer Lifetime Value at IBM," *Marketing Science* 27, no. 4 (2008): 585–99.

In a pilot study implemented for approximately 35,000 customers, this approach led to reallocation of resources for about 14% of the customers as compared with allocation based on past spending history, the metric IBM had previously used to target customers and allocate resources (**Figure 9**). The CLV-based resource reallocation led to a tenfold increase in revenue (amounting to about $20 million) without any changes in the level of marketing investment.

Figure 9. Benefits from CLV-based resource allocation.



Conclusion

Managers must understand their marketing efforts as precisely as possible to determine how much to spend on each marketing channel. If paid search advertising is the most effective way of getting a firm's message in front of the right customer, why would the company spend more on print advertising? If sales calls are profitable only up to a point, the marketing manager must know at which point the calls start costing the company money instead of making it.

The only way to measure the effects of marketing efforts on profitability is through the best-guess relationships revealed through marketing analytics. By using statistical analysis techniques, firms can use past customer behaviors to predict how customers will react to different marketing channels; managers can then optimize spending on each channel.