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Optimizing the end-to-end value chain through demand shaping and advanced customer analytics

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Abstract

As supply chains become increasingly outsourced, the end-to-end supply network is often spread across multiple enterprises. In addition, increasing focus on lean inventory can often create significant supply/demand imbalances over a multi-enterprise supply chain. This paper discusses a set of integrated analytics for supply/demand synchronization with a new emphasis on customer facing actions called demand shaping. Demand shaping is the ability to sense changing demand patterns, evaluate and optimize an enterprise supply plan to best support market demand and opportunity, and execute a number of demand shaping actions to "steer" demand to align with an optimized plan. First, we describe a multi-enterprise cloud-based data model called the Demand Signal Repository (DSR) that includes a tightly linked end-to-end product dependency structure as well as a trusted source of demand and supply levels across the extended supply chain. Secondly, we present a suite of mathematical optimization models that enable on demand up-selling, alternative-selling and down-selling to better integrate the supply chain horizontally, connecting the interaction of customers, business partners and sales teams to procurement and manufacturing capabilities of a firm. And finally, we describe findings and managerial insights from real-life experiences with demand shaping in a server computer manufacturing environment.

Keywords: Demand shaping, product substitution, configure-to-order, mixed choice models, supply chain visibility.

1. Introduction

In today's competitive and dynamic business environment, companies need to continually evaluate the effectiveness of their supply chain and look for ways to transform business processes to achieve superior customer service and higher profitability. Imbalances between supply and demand are the primary reason for degraded supply chain efficiency, often resulting in delinquent customer orders, missed revenue, and excess inventory. This paper describes a novel supply chain planning and execution process that incorporates demand shaping and profitable demand response to drive better operational efficiency of the supply chain. The proposed methodology aims at finding marketable product alternatives that replace demand on supply-constrained products while minimizing expected stock-out costs for unfilled product demand and holding costs for left-over inventory. While most prior related literature focuses on the concept of Available-To-Promise (ATP) where a scheduling system determines a particular product's availability, this paper proposes a customer-centric approach based on customer choice modeling and demand shaping to dynamically incorporate product substitutions and up-sell opportunities into the supply-demand planning process.

Demand shaping is a demand-driven, customer centric approach to supply chain planning and execution. The aim is to align customer's demand patterns with a firm's supply and capacity constraints through better understanding of customer's preferences which helps influencing customer's demand towards products that the firm can supply easily and profitably. Demand shaping can be accomplished through the levers of price, promotions, sales incentives, product recommendations, or on the spot upgrades / discounts to enables sales teams to close deals for in-stock products.

The underlying principles of demand shaping are centered on three competencies:

- Customer preference and demand pattern recognition
- Supply capability analysis that provides improved visibility to the sales force on in-stock and out-of-stock products
- Optimal demand shaping based on advanced customer analytics that estimate propensities of customers to purchase alternate products so that the sales force can guide customers to “next-best” product options

Detecting customer preferences and demand patterns relies heavily on predictive analytics and automated gathering of sales data from every customer touch point, including retailer point-of-sales data, channel partner data, and shopping basket or checkout data from e-Commerce sales portals. Such data is often stored in a so-called Demand Signal Repository (DSR), a cross-enterprise database that stores sales data in a format that allows for easy retrieval of information so that a firm can easily query the database to identify what's selling, where, when and how. Supply capability analysis provides timely information on available product supply to identify imbalances between customer demand and available supply. The third competency of optimal demand shaping is to steer customer demand to a preferred set of products that optimizes the firm’s profitability and revenue while increasing overall serviceability and customer satisfaction.

In this paper, we propose a methodology for demand shaping based on mathematical models that aim at finding marketable product alternatives in a product portfolio that best utilize inventory surplus and replace demand on supply-constrained products. We explicitly analyze customer expectations in a dynamic setting utilizing a customer choice model that determines how customers evaluate product substitutions if their initial product selection is unavailable. Moreover, we present numerical results that attempt to quantify the business value of demand shaping in a configure-to-order (CTO) supply chain where end products are configured from pluggable components, such as hard disks, microprocessors, video cards, etc., an environment where demand shaping is most effective.

2. Related Literature

The demand shaping approach we discuss in this paper has connections to several problems in related literature streams. Ervolina and Dietrich (2001) describe an application of the implosion technology for order promising in a configure-to-order (CTO) manufacturing environment. Building on this approach, Dietrich et al. (2005) develop a deterministic implosion model that identifies suitable product configurations for an Available-to-Sell process that consume the most surplus inventory and require minimal additional component purchasing costs. Market demand, customer preferences, or product substitution policies are not considered in their model. Chen-Ritzo (2006) studies a similar availability management problem in a CTO supply chain with order configuration uncertainty. Ervolina et al. (2009) employ integer programming to identify marketable product alternatives in a product portfolio that best utilize inventory surplus and replace demand on supply-constrained products. Yunes et al. (2007) apply a customer migration model in conjunction with mixed-integer programming to determine the optimal product portfolio at John Deere and Company. A customer migration list contains alternative product configuration choices if a customer's preferred product selection is unavailable. Balakrishnan et al. (2005) apply concepts from revenue management to investigate how a firm can maximize profits by shaping demand through dynamic pricing. Liu and van Ryzin (2008) discuss choice-based optimization in the context of network revenue management, and present a static linear programming approximation that relates to the approximate dynamic programming formulation presented in this paper. Dong et al. (2009) employ a stochastic dynamic programming formulation to study inventory control of substitutable products. Finally, Bernstein et al. (2011) present a model of assortment customization, similar to the choice-set manipulation that we model as a possible lever for demand shaping.

3. Customer Choice Model

In addition to the product-level demand patterns that can be derived from sales data collected at customer touch points, demand shaping requires a detailed model of customer decision-making that can be used to predict the success rate of various shaping actions. We model customers' product choices using a discrete-choice framework that casts the likelihood of all possible purchase decisions within a parametric form. Our framework incorporates product attributes, customer characteristics, and additional market signals that may effect customer decisions. The resulting *customer choice model* depicts latent inter-product relationships, and is combined with up-to-date product-level forecasts to give a full picture of demand.

Product demand forecasts and customer choice modeling are integrated into a two-stage decision process for customer purchases. The first stage occurs prior to demand shaping and involves determination of an *unshaped product choice* for each customer. Our assumption is that the distribution of unshaped product choices is, with the exception of some random forecast error, represented accurately by product demand forecasts that are generated through the traditional planning process. We then allow for a second decision stage in which some portion of this forecasted demand is re-allocated by various shaping actions that are applied across the product portfolio. The end result is a *shaped demand* that we expect to observe post-shaping. The customer choice model is used to predict the degree of redistribution that can be achieved through each possible set of shaping actions.

3.1. Representation of Substitution Probabilities

Customer choice analytics support optimization of shaping actions by generating a matrix of *substitution probabilities* to reflect the rate of demand redistribution between product pairs for any potential collection of shaping actions. To start, customers are segmented by a combination of customer characteristics and unshaped product choice. The set Y provides a collection of observable customer profiles, used to group customers by attributes such as, e.g., sales channel, industry segment, length of relationship, etc. For each type $y \in Y$, we obtain at time $t \in T$ an unshaped forecast F_{tyj} of demand for each product j in the product portfolio J. This allows a further segmentation by unshaped product choice, so that shaping actions are targeted at a segment $s \in Y \times J$, with a forecasted segment size n_{st} equal to the corresponding unshaped forecast. Let $S = Y \times J$ and partition so that S_y contains those segments with customer type *y*.

For each segment s, we operate within a set A_s of admissible shaping actions. An example of a possible shaping action in A_s is to "offer product *i* to segment *s* customers at a 20% discount". As each segment relates to a specific unshaped product choice *j,* actions for that product are intended to redistribute some portion of product *j*'s demand to elsewhere in the portfolio. Since multiple actions may be applied simultaneously, we define an *action profile* $h_s \in H_s \subseteq 2^{A_s}$ to characterize the full set of shaping activities targeted at segment *s*. For each action profile, we provide the optimizer with the following representation of demand redistribution:

$V_s(h_s)$: a |*J*|-vector of substitution probabilities, such that V_{si} is the proportion of the unshaped demand from segment *s* that is redistributed to product *i* when the action profile h_s is applied.

As a result, we are able to represent the predicted shaped demand for any set of segment-specific action profiles as $\tilde{F}_{ty}(\{h_s\}_{s\in S}) = \sum_{s\in S_y} n_{st} V_s(h_s)$, where $\tilde{F}_{yt}$ itself is a |*J*|-vector of shaped product demands.

As is often done in the discrete-choice literature (Kök and Fisher 2007), we can decompose the vector $V_s(h_s)$ into the product of a substitution-structure vector $B_s(h_s)$, and a substitution-rate parameter $\delta \in [0,1]$. The parameter δ is an important measure of the overall substitutability between products in the market. In our numerical tests, we will explore the degree to which effective shaping is dependent on a high value of δ. First, we discuss the estimation of $B_s(\cdot)$ from historical orders and customer data.

3.2. Estimation with Mixed Logit Models

For any significant number of products and actions, the large number of required substitution probabilities makes direct estimation of these values prohibitive. Instead, we derive all of the necessary terms from a discrete-choice model containing far fewer parameters. An important element of this model is the ability to accurately represent customer heterogeneity. In particular, substitution patterns reflect the degree to which products draw from overlapping customer pools, which can only be captured meaningfully through a heterogeneous model. To this end, we employ a mixed logit model of demand (McFadden and Train 2000), which extends the standard logit model (McFadden 1974) to incorporate variation in customer preferences.

We fit a demand model for each customer type *y*, using historical orders from the customer set K_y over the time horizon, T_{Hist}. As with the standard logit model, the mixed logit model predicts order probabilities as a function of product attributes. At time *t*, customer *k* has a stochastic valuation of each product *j*, denoted $u_{kjt} = \alpha_k^T x_j + \beta_k z_{kjt} + \varepsilon_{kjt}$, where x_j contains product attributes, z_{kjt} contains information on shaping actions applied at time *t*, { α_k, β_k } are model parameters to be estimated, and ε_{kjt} is a stochastic error term. In the server environment that we model, attributes in x_j include, e.g., CPU speed, hard drive capacity, hard drive speed, and GB of memory. The second data term, z_{kjt}, contains factors impacting purchasing that may be manipulating through shaping actions. In the simplest case z_{kjt} equals the price p_{kjt}, but this vector can be expanded to encompass quoted order lead-times, marketing intensity, and other relevant factors.

Under the logit assumption that ε_{kjt} are i.i.d. extreme-value distributed, the likelihood of purchase for product *j*, assuming a choice-set J_{kt} of available products, is:

$$L_{kjt|J_{kt}}(\alpha, \beta, x, z) = e^{\alpha_k^T x_j + \beta_k z_{kjt}} / (1 + \sum_{i \in J_{kt}} e^{\alpha_k^T x_i + \beta_k z_{kit}}) .$$

Whereas, in the standard logit model, α and β are constant across customers, the mixed logit model allows for these values to vary across the population according to a specified mixing distribution $G_y(\alpha, \beta \mid \theta)$, whose parameters can in turn be estimated. This can be a continuous distribution, i.e. a normal or lognormal distribution, or a discrete distribution, which then gives rise to distinct latent customer segments. In practice, we combine a discrete component of preference variation, which introduces multi-modality into our preference distribution, with a continuous component that is more economical in its use of parameters. The full parameter vector θ is then estimated along with α and β using a maximum likelihood procedure with our historical order set. In this case, simulation must be used to evaluate $E_{G_y}[L_{kjt|J_{kt}}]$, since this quantity no longer has a closed form.

Under the mixed model of demand, customers' unshaped product choices reflect on their personal values of α and β, giving insight into each customer's sensitivity to shaping actions, and the likelihood of accepting specific substitutes. By conditioning the mixing distribution on each customer's unshaped product choice *j* (e.g., Revelt and Train (1999)), or more generally, on their history of product choices, we obtain an individualized mixing distribution, $G_{y|j}$, that is used to assess various targeted action profiles. In particular, we associate, with each action profile h_s, a shaping attribute vector $\tilde{z}(h_s)$ and an alternative product set $\tilde{J}(h_s)$. The likelihood of a segment *s* customer, where this dictates a type *y* and unshaped choice *j,* accepting substitute *i* when shaping profile h_s is applied, is then provided by the expected value $E_{G_{y|j}}[\, L_{kit|\tilde{J}_{kt}(h_s)}(\alpha, \beta, x, \tilde{z}(h_s))]$.

This quantity is computed to populate the i^{th} entry in $B_s(h_s)$.

4. Demand Shaping Optimization

Having outlined customer behavior and the effects of shaping actions, we turn in this section to a description of the optimization model that selects our recommended shaping actions. The optimization is based on a stochastic view of demand forecasts and is formulated as a Markov decision process. Because of the large size of the model, we solve it using approximate dynamic programming.

As described above, demand is shaped in the context of a manufacturer which purchases and inventories individual components and then uses them to assemble and sell products. The demand is shaped over a sequence of time periods, which is indexed as $t = 1,2,\ldots$. The set of all component types is denoted by C and the set of all products, as above, is denoted by J. The bill of material is represented by U; that is each product $j \in J$ is assembled of $U(j,c)$ components of type c. Components that are not sold are inventoried; the inventory of a component c at time t is denoted $I_t(c)$.

The planning horizon is infinite and future returns are discounted by a given discount factor γ. The purchase of each component is subject to a moderate lead-time l, which we assume to be identical across components. The order size cannot be changed once it is placed.

Demand shaping, as considered in this paper, can address two main types of the supply-demand imbalance: 1) deterministic imbalance, and 2) stochastic imbalance. A deterministic imbalance is known in advance of the lead time for most components, but the supply constraints do not allow to fully satisfy the demand. This kind of imbalance typically occurs after an introduction of a new product or during a long-term component shortage and it may be mitigated deterministically in advance. Stochastic imbalance is not known in advance and only becomes known after it is too late to adjust component supply. This kind of imbalance can be caused by an incorrect demand forecast, an unexpected last-minute supply disruption, or incorrect planning.

Deterministic and stochastic imbalances in the supply chain not only have separate causes, but also require different solution approaches. Since a deterministic imbalance is known within the lead-time of most components, the demand can be shaped into other products and the supply can be adjusted accordingly. Since a stochastic imbalance occurs only after it is too late to modify the component supply, it can only be mitigated by keeping appropriate inventories and shaping the excess demand into products that are available in the inventory. The model described here addresses both deterministic and stochastic supply-demand imbalances.

Components are ordered based on a build-to-order supply policy—that is the supply matches the expected demand. This assumption is made to simplify the model; in most actual applications, the orders would be based on the solution of a newsvendor optimization problem. The actual solution that we use is based on approximate dynamic programming and in essence generalizes the news-vendor solution to multiple stages. Since the supply is assumed to match the product demand, we can ignore component supplies in our model. In addition, all unused components are automatically inventoried with no expiration.

We model the customers using the customer-choice model defined above. In particular, the set S represents the customer segments with a forecasted size n_{st} at time t for a segment s. The forecast is assumed to be made at time $t-l$, the latest time when the supply can be adjusted. Because the forecast must be made in advance, we allow for stochastic disturbances Δ_t in demand, which will lead to imbalances between supply and the unshaped demands. As a result, the realized segment size is a random variable N_{st} with mean n_{st}. The realization of this value at time t becomes known only at time $t+1$.

The realized demand disturbances are normally distributed with mean 0. The distribution used in the model can be arbitrary and can be fit to historical data. The variance of this distribution depends on an external stochastic process of demand variability. Here, we consider a single-dimensional model of variability, denoted ϑ. The variability itself evolves as a normally distributed martingale with fixed variance and zero mean. The demand disturbances Δ across the products are usually negatively correlated with a larger variance in individual products than the total demand. We use Δ_ϑ to denote the covariance matrix.

The realized, unshaped customer demand is modified by taking shaping actions from the set H_s; which includes a no-shaping action option. As described above, the probability of a customer from segment s buying a product i after a shaping action h_s is taken is $V_{si}(h_s)$. Applying action profiles $\{h_s\}_{s\in S}$ at time t results in a realized, shaped demand of $\tilde{D}_{ty} = \sum_{s\in S_y} N_{st} V_s(h_s)$. At the start of the horizon, $\tilde{D}_{ty}$ is a random vector, whose realization will depend on realized values of N_{st} for $s \in S_y$.

The inventory of component type c is subject to a per-item holding cost $c_H(c)$. Taking any shaping action h carries a fixed cost $c_S(h)$—such as the cost of advertising—and variable costs $c_V(h)$—such as product discounts—which are a function of the segment size. The marginal profit for a product j is $c_M(j)$. Finally, the customer model assumes no backlogging---all demand that cannot be satisfied is lost. The overall objective is then to minimize the sum of lost sales due to the product being unavailable, the cost of shaping actions, and the holding costs.

We are now ready to formulate the stochastic optimization problem. If desired, we allow for specific action profiles to be applied to only a portion of a segment. As such, our decision variables π_t represent the probability of taking each shaping action h_s at every time step t for each segment s. These probabilities are denoted as $\pi_t(s, h_s)$.

The main optimization problem in demand-shaping is stochastic due to the uncertain nature of the demand forecasts and can be modeled as a Markov decision process (MDP) (Puterman 2005). The Markov state at time t is represented by the inventory of all products, the demand variability, and the demand forecast. Demand forecast evolves stochastically as described above; the demand variability evolves as a martingale. The Bellman optimality condition for a value function $v_t(I_t, \vartheta_t, n_t)$ is as follows:

$$v_t(I_t, \vartheta_t, n_t) = \min_{\pi_1, q_1} E\begin{bmatrix} \sum_{c\in C} c_H(c)\cdot I_t(c) + \sum_{j\in J} c_M(j)\cdot \min\{q_t(j), \sum_{y\in Y}\tilde{D}_{tyj}\} + \\ + \sum_{s\in S}\sum_{h\in H}\pi_1(s,h_s)\cdot(c_S(h_s)+c_V(h_s)\cdot N_{s,1}) + \\ + \gamma\cdot v_{t+1}(I_{t+1}, \vartheta_{t+1}, n_{t+1}) \end{bmatrix} \quad (1)$$

Here, we use $q_t(j)$ to represent how many products can be build from the available components and $\gamma \in (0,1)$ to represent the discount factor.

The optimization variables in the problem above are constrained as follows. The first constraint ensures that the shaped demands $\tilde{D}$ are based on the shaping action probabilities π:

$$\tilde{D}_{tyj} = \sum_{s\in S_y}\sum_{h_s\in H_s} N_{st}\cdot V_{sj}(h_s)\cdot \pi_t(s,h_s) \quad \text{for all } y\in Y \text{ and } j\in J.$$

The second constraint ensures that the number of the products sold corresponds to the inventory of each component type:

$$q_t(j)\cdot U(j,c) \le I_t(c) \quad \text{for all } j\in J \text{ and } c\in C.$$

Note that due to the assumption of the supply matching the deterministic demand n, we can assume that the demand with no shaping is 0. This assumption allows us to study the effects of stochastic imbalances alone and can be easily relaxed. There are additional constraints that ensure that the probabilities of shaping actions in each segment sum to 1 and that the inventories are correctly tracked across time periods.

The optimization problem in Eq. (1) is too large to be solved directly because the value function is defined for continuously many states. Instead, we solve the MDP using approximate linear programming, which is a version of approximate dynamic programming (Powell 2008). Normal distributions are approximated by the Gauss-Hermite quadrature. The shaping decisions are then chosen greedily with respect to the approximate value function.

5. Numerical Experiments

In this section, we evaluate the effectiveness of demand shaping, as it is depicted in Sections 3 and 4, in minimizing backlogging costs that result in the presence of unbalanced supply and demand. We simulate a production/sales environment that is modeled on a realistic problem setting taken from IBM's server supply chain. The simulation has two parameters – the demand variability ϑ and the substitution rate δ – that may be altered to create alternative settings. Within this two dimensional space, we compare the expected backlogging costs that arise both with and without shaping to assess the value of shaping optimization, and to highlight its sensitivity to the two control parameters.

The details of our simulation are as follows: we begin with true historical forecasts and realized customer orders from the hard drive options portfolio supporting IBM's System X line of servers. We link the forecasts directly into the above model to populate F, while we use customer and order data to estimate a substitution structure framework B. We assume a baseline level of supply that exactly covers the forecasted demand, but simulate the stochastic process Δ of demand disturbances to induce supply imbalances, with the potential to correct these through shaping. Our product set consists of 16 hard drives, and we model customer decisions on the basis of hard drive capacity, speed, interface type, and – a potential shaping lever - price. We assume that any unfilled demand will result in lost sales, and evaluate supply chain performance by the percentage of sales that are lost. Results are averaged across 15 simulation runs for each setting. Simulations cover a 30 week horizon, with a discount rate $\gamma = 5\%$ and a cost of 1% of unit revenue for holding inventory across periods.

Figure 1 plots the percentage of sales lost across a range of simulation environments. Each curve is generated at a particular δ (i.e. low, moderate, or high substitutability), and ϑ is varied from zero up to a setting with a coefficient of variation of 22.5% for each product demand. The $\delta = 0$ case provides a baseline where no demand can be shaped, and the improvement from this case illustrates the *value of shaping* in each setting.

The directions of performance improvement for our shaping optimization are quite intuitive. As variability is increased, there is a greater inherent mismatch between forecasts and realized demand. This increases lost sales in all settings, but also presents a larger opportunity to increase performance through shaping. As such, the value of shaping, measured by the performance gap from the $\delta = 0$ case, widens with increasing ϑ. In conjunction, shaping actions become more effective as the degree of substitutability between products is increased, so that the value of shaping increases in the direction of δ as well. When both variability and substitutability are high, the impact of shaping can be dramatic. For example, with high variability and $\delta = 1$, we observe a reduction in lost sales from 13.1% down to only 2.4% with shaping.

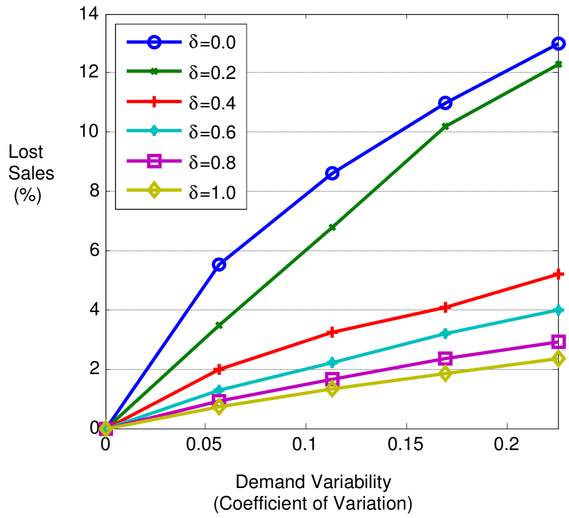

Figure 1: Percentage of sales lost in simulated experiments with demand shaping.

As substitutability is increased from 0, we observe a sharp jump downwards in lost sales resulting from only weak substitutability. For example, in the high variability case, shaping with a conservative substitution rate of $\delta = 0.4$ delivers a relative reduction of 60% in lost sales compared to not shaping. It thus appears, from a product assortment perspective, that only a modest amount of substitutability is needed to successfully implement demand shaping. Interestingly, this result provides something of a demand-side analog to the result of Jordan and Graves (1995) on the steepness of initial returns to production flexibility. A deeper analysis of the interactions between demand shaping and production flexibility may indeed prove worthwhile for future study.

With regards to variability, we observe that the gap in lost sales between each δ curve and the no-shaping curve will increase with ϑ in most cases (the exception is with $\delta =$ 0.2, where the gap increases at first, before reaching a threshold where it seems that potential shaping actions are being exploited fully). Despite this trend in performance, it is apparent that additional variability drives a steady increase in lost sales percentage along each curve. Thus, while shaping can soften the deleterious effects of mismatched supply, a comprehensive approach aimed at improved forecast accuracy and/or reduced lead-times is most beneficial. To this end, however, we note that demand shaping will often be the simplest of available measures to implement, and may come at a relatively small cost to the manufacturer. With a strictly supply-side focus, the investment required to achieve a comparable reduction in lost sales can often be prohibitive.

6. Conclusion

In this paper, we have described a mathematical model for demand shaping that aims at finding marketable product alternatives in a product portfolio that best utilize inventory surplus and replace demand on supply-constrained products. We outlined demand shaping actions that improve inventory positions with early and efficient actions to address surplus materials, and shift demand to available and profitable products through dynamic pricing. Our numerical results showed that more flexible customers are more profitable customers. Market intelligence and data analytics can identify these more flexible customers via market models. For example, a very price-sensitive client may only be presented with two sales recommendations – both of which are alternative-sells or one alternative sell and one down sell. A more price insensitive client may be presented with five dynamic sales recommendations – three are up-sells and two are alternative sells (no down sells). This stratification of clients by price sensitivity and the approach to dynamic sales recommendations will be essential to achieving the business results we have identified.

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