Travelocity Becomes a Travel Retailer

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In 2002, Travelocity lost revenue and market share to competition as the business environment changed. Travelocity and Sabre collaborated to develop the enterprise network model (ENM). The ENM combines discrete choice customer modeling with simulation and large-scale optimization to improve Travelocity’s management supplier agreements, customer marketing, and product pricing. The ENM has helped Travelocity become a more effective retailer and has contributed over $54 million to Travelocity earnings, at a current rate of $43 million per year.

Key words: industries: transportation, shipping; marketing: buyer behavior.

With approximately $80 billion in travel products sold worldwide in 2005, Sabre Holdings is the world’s largest travel-distribution system, providing an electronic marketplace in which consumers and travel agents shop for and buy products from travel suppliers, such as airlines and hotels. In 1996, Sabre launched Travelocity, an online travel company that leverages Sabre’s travel experience and technology to sell travel products directly to consumers. Travelocity’s original business model was based on earning commissions from selling airline tickets and revenues from selling advertising space. Because commissions were consistent across suppliers, we were mostly indifferent to what ticket suppliers sold or who advertised on our site. Travelocity initially took the lead in Internet airline ticket sales, but as new competitors entered the space, Travelocity’s share of travel bookings steadily eroded. Some new entrants established competitive advantages by introducing unique content, such as Expedia’s merchant hotel program, Orbitz’s Web fares, and Priceline’s opaque air. Adding to Travelocity’s loss of market share in 2001, the airlines eliminated or greatly reduced commissions in early 2002.

Because online retail was a new channel for the travel industry, very little by way of tools, processes, or analytics existed to support supplier-retailer partnerships or to optimize retail operations. Prior to late 2002, Travelocity could not even calculate its own airline revenues but rather relied on suppliers to inform it of earned commissions and overrides several weeks after the end of the reporting period. Travelocity was in danger of extinction if it stuck with its original model of passive consignment.

To survive in this new environment and to avoid dying as had most Internet companies, Travelocity had to become a sophisticated retailer by negotiating marketing agreements with suppliers, managing access to content, and expanding into more profitable lines of business. In May 2002, then-president of Travelocity, Sam Gilliland, asked the Sabre Research Group to help Travelocity adapt to the evolving environment and increase its sophistication as a retailer. The plan was to develop decision support
by (1) understanding the online retail travel business, (2) identifying the drivers and calibrating their influence on online retail profitability, and (3) developing the capability to forecast and influence future performance. This approach led to the development of the enterprise network model (ENM).

Like many retailers, Travelocity based its value proposition on connecting suppliers and customers. Travelocity’s store is its Web site, www.travelocity.com, and its business performance depends on getting the right products into the store through relationships with travel suppliers, getting the right customers into the store through branding, promotions, and advertising, and then providing accurate, compelling responses to customer’s requests. Travelocity competes with online travel agencies, such as Expedia and Orbitz, distressed inventory outlets, such as Priceline and Hotwire, and supplier Web sites, such as NWA.com and Hilton.com. Because suppliers and customers have multiple relationships in this marketplace, changes in content, display, or price can dramatically affect market share and revenues.

The Sabre-Travelocity team developed the enterprise network model to improve decision making in this environment. We took advantage of the data available from the Travelocity site and from competitors. We developed customer models (Figure 1) to estimate consumer preferences for product quality, price, brand, and promotion. We developed supply models to evaluate supplier deals and manage the display of flights and fares in the store. We developed models relating to price and the management of available content. Finally, we developed marketing models to identify compelling travel opportunities and inform our customers of them.

The online retail environment is very dynamic with opportunities developing and evolving rapidly. The need to react quickly made the traditional process of describing requirements, developing models, and implementing them unworkable. We used a method of applying general principles to a direction for improvement. We began projects by using the available data and making a series of quick hits rather than by making a single long-term comprehensive effort. We based our approach on proof-of-concept projects in which we tried to quickly determine whether a problem was solvable. If the solution we created proved to be effective, scalable, and transferable, we invested in refining it further. Our initial models were often spreadsheets. We used them while we developed more robust solutions. Some projects never progressed beyond the proof-of-concept stage because the spreadsheets were appropriate. For some projects, we developed operational prototypes that had automated data feeds, graphical user interfaces, and ongoing support. This flexible and progressive process has delivered value for several years. Since 2002, the ENM has yielded over $54 million of incremental value, with a current annual run rate of $43 million. The team that developed the ENM consisted of about five people working for three years.

Customer Data and Modeling

Our initial priority was to improve our understanding of Travelocity’s customers, in particular, their purchasing behavior. We needed to know how product quality, price, promotion, and placement of screen displays affect purchase behavior, which in turn affects Travelocity’s market share and revenue. For example, how attractive is a $100 connecting fare for a 10:00 AM departure on a low-cost carrier versus a $200 nonstop fare at 2:00 PM on a major airline? Travelocity had already developed a click-stream database for...
accounting purposes and for analyzing system problems. These data were a potential goldmine of insight, but they had never been used to analyze customer shopping patterns. We initially developed a customer-choice model that predicted which displayed option a customer would purchase, given that the customer purchased something. We next focused on conversion rates, the probability the customer would buy something instead of leaving the site without making a purchase. These models worked well in our initial applications, but we learned that conversion is largely a function of what is available from our competition. We developed robots to shop selected markets on competitors’ Web sites and log the results. Their data and the resulting analysis were crucial to understanding the impact of price and display on Travelocity bookins and market share.

For every shopping session (over 500,000 per day), Travelocity stores each shopping request the customer made, each screen displayed in response to the request, and the next request the customer made (after viewing the screen), all in sequential order. From this information, we can determine (1) what each customer requested (demand), (2) what was displayed to each customer (choice set), and (3) and what each customer did (action).

**Discrete Choice Models**

To model booking behavior, we use multinomial discrete choice (also called conditional logit). Here, one observation consists of a screen of itineraries, and the model assigns a purchase probability to each option. The variables in our choice model are fare, number of connections, carrier, elapsed time, and departure time. We compute utility score as a linear function of the attributes of each choice (such as flight option displayed):

\[ U_i = \sum_{j \in A} \beta_j \text{Attrib}_{i,j}. \]

We calculate predicted probability for any one option being chosen as

\[ MS_i = \frac{e^{U_i}}{\sum_{k \in \text{ChoiceSet}} e^{U_k}} \]

(Ben-Akiva and Lerman 1985).

After fitting our first model, we realized that many options were clearly inferior and would never be booked. Online travel Web sites display many options, and traditional choice modeling assigns some positive probability to each. As a result, we overestimated the purchase probability for many poor (dominated) choices and underestimated the purchases from reasonable (or viable) itineraries. Dominated choices are those that no rational customer would select, for example, a set of connecting flights that costs more than a nonstop flight (with the same departure time and airline). We used data envelopment analysis to identify and remove dominated choices (Cooper et al. 2005).

The models discussed so far assume that all customers are identical, but we know that different types of customers travel for different reasons. To complement these models, we introduced customer-segmentation rules. We started by fitting our choice models by segment to account for different behaviors. We initially used a business-versus-leisure segmentation created for Travelocity by Kestnbaum Analytics (www.kestnbaum.com). For our recent work, we developed latent-class-choice models (Magidson and Vermunt 2002) that allow simultaneous segmentation and choice modeling. We fit a latent-class model across about 200 markets, and not only did it fit improve, but the resulting segmentation provided new insights.

**Conversion Models**

To predict the impact of changing prices and displays on Travelocity bookings and revenue, we needed to understand what factors affected customers’ likelihood of booking. We started with exploratory data analysis and then developed a logistic regression model that predicts conversion rate (the probability that a shopping session ends with a sale). Most of the results we obtained were not too surprising. Before making any purchase, most travel customers shop around. As a result, the probability of customers making a purchase depends on the utility of the items on Travelocity’s screen versus the utility of those of our competition. There are also nondisplay factors, such as number of days prior to departure, the time of day that a customer shops, the day of week, the market type (business versus leisure), prices compared to recent prices, and Web site response time, that affect conversion rates.

The impact of response time was surprising. Sabre and Travelocity had speculated that response time
affected conversion rates, but no one had proven that reducing response time would actually increase conversion rates and bookings. After adjusting for the other known effects in our model, we were able to isolate the impact of response time. It was much larger than we had expected. Because of these findings, we realized that it was important to reduce response time in redesigning Travelocity’s air-shopping process. The new system cut response time by over 30 percent and increased conversion rates by 55 percent. Most of the new system’s increase in conversion rates was due to improved functionality. Our analysis indicated that 20 percent of the conversion rate increase (11 percent out of the 55 percent) came from reducing the response time. This 11 percent increase in the conversion rate produced an additional $12 million in air booking revenue in 2005 with an expected benefit of $12.3 million in 2006.

Deal Evaluation and Display: Supply Model

As the airlines reduced their commissions to retailers, Travelocity had to (1) negotiate multiple, often conflicting, agreements, and (2) manage airline sales to maximize the value of these agreements. We developed the supply model to support both of these goals.

Travelocity revenues from air sales come from commissions, incentives, and service fees. Commissions can be fixed dollar amounts or percentages of fare values for tickets. Airlines pay incentives only if Travelocity reaches certain performance (typically market share) targets. Revenues from commissions and service fees (paid by the retail customers) are driven by sales volume; incentives are driven by sales mix. Incentives are large lump sums that the airline pays in full when the retailer reaches the target or at the end of the measuring period or not at all. Therefore, making or not making a performance target can greatly effect Travelocity’s air revenues and earnings. Travelocity has an array of merchandising tools, such as promotions, e-mail campaigns, and screen order, that it can use to shift demand. Merchandising planning and operations decides which carrier to promote in which market, how, and when. Marketing this decision is a very large problem complicated by a variety of issues. Travelocity serves over 25,000 markets (a market is one origin-city/destination-city combination, such as New York to Los Angeles), and it has one or more performance deals with every large US domestic carrier. These deals create conflicting objectives when flight networks overlap. As a consequence, Travelocity cannot achieve all performance targets simultaneously. Instead, it must decide which performance targets to pursue. Airlines offer either standard commissions with no bonus incentives or high incentives with lower commissions. If Travelocity changes the flight displays shown to consumers to shift bookings to a preferred carrier, then Travelocity’s bookings on other carriers will decrease. Travelocity has only limited control over which carrier’s demand it reduces because providing poor screen display of desirable content may result in loss of sales.

Finally, at any time during the measurement period, the future demand, the effectiveness of merchandising tools, and the exact number of sales needed to reach a given performance target are unknown. Travelocity takes actions that maximize expected revenue across a set of likely outcomes.

Travelocity’s revenue-planning department uses the supply model to support the following business functions:

—To control displays, it determines which flights to display in response to a customer request to achieve its growth and demand-shift targets.

—To plan and negotiate deals, it determines the net-revenue impact of a new or modified deal considering all existing and pending deals.

—To determine the impact of carrier liquidation or a carrier’s withdrawing or adding content (flights), it takes action to maximize the opportunities and minimize the costs associated with such scenarios.

Supply Model Implementation

We began the supply model as a spreadsheet and gradually developed it into a comprehensive system built around a large-scale mixed-integer program (MIP), the demand optimizer. Customer models and booking forecasts provide input to the demand optimizer. The demand optimizer produces controls for air-shopping displays, recommendations for promotions, financial projections, and information to support airline contract negotiations (Figure 2).

The model forecasts airline booking based on a combination of historical booking patterns (profiles)
and current bookings. We use a representative set of shopping sessions and the customer-choice model (CCM) to predict the impact of price and content changes on Travelocity bookings. The demand optimizer is a large-scale MIP with the objective of maximizing expected total revenue (appendix).

We developed the ENM in stages. First, we developed a proof-of-concept model in OPL (ILOG 2000) with an Excel interface. It captured Travelocity’s top 5,000 markets, grouped airlines into eight distinct groups, and accounted for one booking and one travel period. The model contained continuous shift variables, 30 integer variables representing levels of performance deals, and 120,000 constraints. In the next version of the model, we captured all 25,000 markets and 20 airlines, modeling six months of bookings and travel. Instances of this model contained over 630,000 shift variables, 300,000 growth variables, 1,300 performance-deal-level variables, and 1.9 million constraints.

We solved the demand optimization model using CPLEX 8.0 (ILOG 2002). We initially limited preprocessing to identifying the maximum and minimum performance level attainable for each incentive deal. We determined a deal’s maximum (or minimum) attainable performance level by evaluating the performance measure after shifting all possible demand to (or from) the carrier associated with the deal. The effectiveness of this preprocessing depended on shift potential, deal structure, and time remaining in the measurement period. In some cases (close to the end of the measurement period), we could determine a deal’s performance level after only preprocessing. For the biggest problem instances, this approach took more than five hours to solve. While this solution time is acceptable for managing deals and for financial forecasting, it is not acceptable for evaluating deals, when the analyst must set up and solve various problem instances during the ongoing negotiations.

To solve the problem faster without sacrificing solution quality, we developed a two-stage solution approach based on the following observations. First, the differences in any two carriers’ commissions are very small relative to incentives. Second, shifting demand
in a market affects all the incentive deals covering the market. By aggregating all the markets covered by a set of performance deals, we could estimate the impact an equal shift across all these markets would have on deal performance.

In the first stage, we aggregate markets and solve the problem at the aggregate level. In particular, we partition the set of all markets into regions such that all the markets in a given region are covered by the same set of performance deals. We formulated the demand optimization model on the region level by rolling up market-level demand, shift potential, and per-booking revenues appropriately. This model has the same number of binary variables as the original model but considerably fewer continuous variables. We use the solution to this region-level model to fix binary deal variables (to zero) in the original model. For each deal, only the variables that represent the payout level achieved in the region model and the next lower level remain unfixed. We then solve the original model over the reduced solution space. With this staged approach, we can solve all problem instances in 15 minutes or less. We solved some of the instances using the original approach to get a better understanding of solution quality. With this staged approach, we found the optimal solution for all the test instances. Moreover, the solution to the region model achieved 90 percent or more of the optimal increase in revenue over the base.

Supply Model Applications
Travelocity used the supply model to pursue more aggressive override deals with lower base commissions but higher performance-based commissions than its existing deals. For example, in 2003 a major US carrier proposed to reduce commissions in exchange for increasing incentive payments. Using the supply model, Travelocity determined the break-even relationship between commission and incentive. Travelocity negotiators thus had a simple but powerful tool with which to evaluate any offers from this carrier. In general, the supply model enabled Travelocity to increase the number of performance-based deals it could accept and profit from; the number of performance-based deals it made increased from five before deployment of the supply model to more than 100 afterwards. In some cases, the supply model supported deals to reduce incentives in exchange for increasing commissions. These enhanced commissions also benefit Travelocity.

Travelocity influences the mix of sales among carriers by adjusting the amount of screen space it gives each carrier as customers shop. After determining targets for shifting bookings, the ENM produces controls that affect Travelocity’s displays for air travel. Travelocity ordains its air display first by fare and then by quality of service. If two or more itineraries are tied with respect to fare and quality, Travelocity uses airline ranks to determine their display order. The display-control optimizer sets more than 40,000 ranks at the market-carrier level to achieve the shifts in demand the demand optimizer recommends. We find that, in our experience, Travelocity can shift airline market share by up to seven share points by using display controls.

Supply Model Impact
Deployment of the supply model greatly increased Travelocity’s revenue from incentives and enhanced commissions (Table 1).

Travelocity also needed the supply model as a tactical tool. For example, in 2002, Travelocity was close to making a performance target but had a reasonable chance of missing the goal. After evaluating the likelihood of the different outcomes, Travelocity decided to purchase tickets from the carrier to ensure that it reached its performance target. It ultimately used the tickets for company travel.

Marketing Models
Making customers aware of great travel opportunities increases site traffic, conversion rates, cross-sell rates, and customer retention. Travelocity reaches customers

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<td>2006 (est)</td>
<td>3.7</td>
<td>2.7</td>
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Table 1: We summarize incremental payments to Travelocity compared to a baseline from the third quarter of 2001 through the second quarter of 2002 (the earliest data available for comparison).
through e-mail, by advertising on other Web sites, and through search engines, call-center agents, and its interactive voice-response system. We improved the effectiveness of e-mail campaigns by monitoring daily airfares and identifying travel situations (markets and departure dates) where prices are compelling, that is, prices at which conversion rates increase. These campaigns, known as good day to buy, greatly increase booking rates compared with nontargeted campaigns.

**Good-Day-to-Buy Models**

Online travel demand comes from discretionary and nondiscretionary consumers. Small variations in price have little impact on nondiscretionary demand. Price reductions below a critical point attract discretionary traffic and can increase booking volumes. When airline or hotel prices drop below this critical or reference point, we initiate good-day-to-buy (GD2B) e-mail campaigns to inform our customers about these good deals.

We developed GD2B models to identify reference airfares and room rates at which price-sensitive customers book air travel and hotel stays. The reference prices are the break points in piecewise regression equations between booking and current price versus a 30-day moving average of prices (Figure 3). Travelocity’s marketing department uses the reference values as rule parameters to identify deals in various markets. We automated the monitoring of daily airfare changes in more than 10,000 markets. We monitor hotel and package rates for top destinations.

Once we find GD2B opportunities, we review Travelocity shopping data to identify customers who shopped recently in these markets but did not book. We also select some customers who bought travel products other than the GD2B product for cross-sell promotions. If a customer qualifies for multiple campaigns, we choose the highest margin campaign. Travelocity designs an e-mail image to communicate each deal and sends it to the customers. The impact of GD2B is summarized in Table 2.

![Figure 3: Small price variations from prevailing fares have little impact on demand. Price reductions below a critical point, the reference fare, attract discretionary demand and can significantly increase booking volumes.](image)

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<th>Year</th>
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<td>6.90</td>
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Table 2: In every e-mail campaign, Travelocity withholds good-day-to-buy (GD2B) information from five percent of the recipients. We estimate the value of GD2B by comparing the booking rate of the customers who have full information against those without full information. GD2B information increases booking rates by 1.14 percentage points.

**Pricing Models**

Travelocity’s initial business was based on an agency model, in which suppliers set prices and paid Travelocity a commission or incentive. Travelocity has aggressively increased its merchant business, business for which Travelocity negotiates with suppliers for access to products (airline seats or hotel rooms) at fixed discounts and marks up the products by adding its own service fees. Travelocity’s profit is based on the spread between cost and price. We used our knowledge of customers’ shopping behavior to mark up two kinds of merchant products, opaque air and packages. Regardless of the model, it is critical to find the best deals for every customer requesting information. For airline tickets, the process is known as low fare search (LFS). In 2004, Travelocity lagged its major competitors in LFS performance. We identified and developed enhancements to LFS that dramatically improved Travelocity’s market share.

**Opaque Air Markup**

Travelocity displays opaque air trips without specific information on the airline and the schedule. At
the time of shopping, the consumer knows the fare and the departure and return dates but not the specific flight times or connecting points. After completing the booking, the consumer receives the full itinerary. Some consumers find this uncertainty unacceptable. Opaque products are cheaper than normal fares, however, and many consumers are willing to buy an opaque product if the price is right. This segmentation enables airlines to generate incremental revenue by selling distressed inventory cheaply without disrupting existing distribution channels or retail pricing structures.

Travelocity had been adding a markup fee based on a fixed percentage of the price gap between the cost of the opaque and the lowest published alternative. We developed a model to set opaque markup fees dynamically based on the alternatives available during shopping. We used the interactive nature of the Internet shopping environment to provide instant markup recommendations. We used customer-choice models to predict the probabilities that a customer would (1) buy an opaque itinerary, (2) buy a nonopaque itinerary, or (3) abandon the Website. We used a multinomial logit choice model (Allison 2001) that incorporates the effects of price, advance purchase, day of the week, and the service characteristics of the lowest nonopaque itinerary.

Our objective was to set the opaque markup fee to maximize the expected profit from each shopping session that included an opaque. We expressed the markup fee \( M \) as a percentage of the difference between the lowest nonopaque fare \( L \) and the cost of the opaque fare \( B \). The expected profit per session is \( M(L - B)p_o + Cp_o \), where \( C \) is the commission on each sale of nonopaque fares, \( p_o \) is the probability of selling the opaque fare, and \( p_n \) is the probability of selling a nonopaque fare \( (p_o + p_n + \text{Prob(abandonment)} = 1) \). The probabilities of sale \( (p_o, p_n) \) are functions of \( M, L, \) and \( B \).

Travelocity displayed only one opaque fare in each session, so we used a line search to find the optimal markup. Before we developed this process, Travelocity used a fairly low markup fee. Our analysis showed that the optimal markup fee was quite a bit higher. Because there was uncertainty in our customer-choice models, Travelocity increased its markup fee but stayed below what we considered optimal because profit drops sharply if the markup fee is set too high. The net benefit of this process was to increase opaque revenues by 48 percent ($3 million per year), compared to the previous heuristic markup approach. Airlines reduced or eliminated opaques after 2003; therefore our benefits, while impressive, were short-lived. Fortunately, we were able to apply some of what we learned to the package markup fee.

**Package Markup**

Travelocity’s servers construct packages while the retail consumer shops, and they contain at least two of the three basic travel components: air, car, and hotel. Package prices are cheaper than the sum of component prices because suppliers offer special merchant fares and rates that are available only if the content is sold as part of a package. The combination of good products and good prices has made this a very fast-growing segment in online travel.

Travelocity designed the markup process for its dynamic package path, called TotalTrip, based on its experience with static packages. When it launched TotalTrip, competitive package pricing information was not readily available and Travelocity’s hotel managers set the hotel markups. As a result, only air markups affected actual package prices. To determine air markups, Travelocity used the lowest available comparable published fare, that is, an airfare available for stand-alone air service as a reference. It considered a published airfare comparable if the underlying itinerary had the same number of stops as the itinerary for which it was computing the markup. If no such itinerary existed, it considered itineraries with the same type of carrier comparable, that is, premium or nonpremium. If the reference fare was below or equal to the package-only airfare, Travelocity marked up the package-only airfare by a fixed percentage. If the reference fare was above the merchant airfare, Travelocity computed two different markups. One consisted of a fixed markup amount and a percentage of the difference between the reference fare and the merchant fare. The other markup consisted of the difference between the merchant fare and the published airfare plus a fixed markup amount and a percentage of the reference fare. Travelocity picked the lower of the two as the final markup.

Prior to implementation, we analyzed this markup process and the parameter settings. To do so, we
created a database of sampled (representative) air-shopping sessions, running each session through a simulation that contained a customer-choice model, a conversion-rate model, and an optimization engine. The conversion-rate model determined the probability that a customer would buy a package from Travelocity given the price and quality of package offerings. The customer-choice model determined the purchase probability for each option offered given that the customer bought something. The optimization engine determined the set of markup fee parameters that maximized total revenue across all sessions. The optimization engine started with an approximate-steepest-edge approach. We computed one-dimensional gradients across a batch of sessions and used them to determine an improving direction of change for the parameter vector. We then performed a line search along this direction starting with a step length that was proportional to the estimated change in revenue. The optimization engine switched to an exact-steepest-edge approach once the approximate approach started oscillating between alternative solutions. In general, the profitability associated with the final solution of the approximate-steepest-edge approach was within one percent of the final solution. The simulation-based optimization allowed us to determine parameters that improved package profitability by five percent.

In developing the markup fee mechanism, we found that (1) two of the six parameters did not add any value to the process, and (2) moving from networkwide parameters to market-specific parameters added value. Travelocity acted on both findings. It dropped the two superfluous parameters and implemented market-level-specific parameter sets. With the recommended rules, Travelocity marked up the packages less than it would have with its original planned rules. After it launched the new markup algorithm, Travelocity tracked conversion rates and market share as well as package revenue. Increases in conversion rates indicated that lowering markups improved revenues by $500,000 during the first six months (July through December 2003). As the TotalTrip business grew, so did the benefits (Table 3).

### Low Fare Search

Our work improved Travelocity’s competitive position in the travel marketplace. However, despite the benefits achieved, Travelocity’s main competitor, Expedia, maintained a 10 percent share advantage in air bookings over Travelocity. The presidents of Sabre Holdings and Travelocity asked us to look for ways to further narrow this gap.

Travelocity’s marketing department had done extensive research to understand the main attributes of purchase behavior for air tickets and found that best pricing is the single most important driver of air ticket purchase behavior. Airline seats are a commodity, and given the ease with which customers can shop with online travel agencies, they look mainly for the lowest fares for their trips. According to a study by PhoCusWright (2004), more than 60 percent of online consumers buy the absolute lowest fare. Forrester Research (Harteveldt 2004) also found that price satisfaction was the most important driver in Web site loyalty. Although such major online Web sites as Travelocity, Expedia, and Orbitz have access to the same airline-published fares distributed in the global distribution systems (GDSs), they use different algorithms to search for the lowest fares, often obtaining different results, which encourages consumers to comparison-shop. Given the importance of low fares and their impact on purchase behavior, we compared the performance of Travelocity’s low-fare search process and that of its major competitors. Our objectives were to determine the sources of the market-share gap, identify improvements, and estimate their potential benefits.

### Determining Whether Travelocity Was Losing and Why

Market-research companies, such as Jupiter Research (Clarkson 2005) and PhoCusWright (2004), found that, among major online travel Web sites, Orbitz led in

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Table 3: Using the package markup optimization, we determined parameters that improved package profitability by five percent, providing additional benefits.
pricesatisfaction, followed by Expedia, and Travelocity. To validate their studies, we collected data on fare competitiveness using robots over a large sample of markets. We collected the shopping data for the same scenarios (that is, origin, destination, departure date, and return date) at exactly the same time to avoid any price discrepancies caused by airline changes in fare availability. We monitored the data over several weeks and confirmed the perception that Travelocity was offering the lowest fares less often than its main competitors, Expedia and Orbitz. We identified two possible reasons for our share gap. First, some airlines give different agencies different fares and greater access to their inventories of cheap seats. Second, agencies use different low-fare-search (LFS) algorithms. Travelocity’s LFS algorithm is based on Sabre’s technology for traditional agencies, whereas Expedia and Orbitz built their own LFS systems.

We did extensive manual analysis and determined that Travelocity and its competitors had almost identical fares and access to airline seats. Low-fare-search technology was the single biggest reason for Travelocity’s pricing losses. We focused on identifying why our LFS algorithm missed the low fares even though we had almost the same content as our competitors.

The Low-Fare Search Process
Searching for low fares may seem like a simple problem, but the number of possible fare combinations and the rules that govern how fares can be combined make it difficult. The basic unit of pricing, a fare, is defined as the price of one-way travel between two cities, regardless of the number of flights involved. Airlines update their lists of fares 10 times daily. With each fare comes a set of rules for its use. Low fares, for instance, often have requirements, such as two-week advance purchase, a connection, or travel at an inconvenient time of day. Rules of another type restrict the way a fare can be combined with other fares. Fares are put together in combinations known in industry lingo as priceable units. A priceable unit is a collection of fares and associated flights that have one of several possible geometries: a one-way trip or a round-trip, for example, or an open-jaw trip, or a circle trip. Still other fare rules could require a round-trip with a Saturday night stay or use in combination with an international flight. Using the techniques of complexity theory, Robinson (2002) showed that for a given fare, it can be NP-hard just to determine what existing flights satisfy restrictions; even if the flights are fixed, the problem of choosing fares to cover flights is NP-hard (Robinson 2002). This problem is further complicated by fare combinability. Consider a request for a round trip from Seattle (SEA) to Chicago (ORD) and back connecting in San Francisco (SFO). The cheapest fare for this itinerary could be that for a SEA-ORD round trip. Alternatively, it could be a SEA-SFO round trip plus a SFO-ORD round trip. Or it could be a SEA-ORD one-way fare plus an ORD-SFO one-way fare plus a SFO-SEA one-way fare. This last combination is known as an online triangle. Even though the itinerary is symmetrical, we could use one fare outbound and two fares for the return. If we substituted a second airline’s flight and fare from SFO to SEA, we would have an interline triangle. All of these types of fare constructions are patterns the LFS process must consider to conduct a complete search. Because the combinations of airlines, itineraries, fares, and constructions are so extensive, brute-force enumeration is infeasible. The Sabre LFS process can respond to 500 requests per second for domestic markets. To respond quickly, it relies on heuristics to explore the search space. We identified 15 potential fare combinations that should be considered during an LFS. Sabre and Travelocity had the capability to consider some of the fare combinations, but by analyzing fare competitiveness data, we found that 60 percent of our LFS technology losses to competitors were caused mainly by failing to explore some fare combinations. The missing combinations were online triangles, interline triangles, and simple interlines (one airline outbound and a different airline on the return).

Estimating the Impact of LFS Enhancements
After identifying the reasons for losses and how they related to the fare-construction capabilities that Travelocity was missing, we estimated the impact of these losses on Travelocity’s share. Because Travelocity had limited simple interline capabilities, its gap in market share compared to its competitors was six to seven times larger than its share gap for online options. This limitation alone explained more than 30 percent of the share gap. Finally, interline triangles showed the lowest impact on share because customers rarely
purchased interline triangles; however, their presence creates a perception of completeness in the LFS results.

Using our customer-choice models, we estimated that adding online triangles and simple interlines to LFS would increase Travelocity’s share between 1.2 and 1.6 percent. We based these estimates of booking-share improvements only on gains from Travelocity’s main competitor, Expedia. (Together, they have about 60 to 70 percent of the domestic bookings obtained by the major online agencies that book tickets through a GDS.)

Implementation and Actual Impact
We implemented the enhancement covering price triangles in October 2005. Travelocity’s booking share gap (versus Expedia) started to drop immediately after implementation. By mid-November, the share gap had dropped from 12.5 percent to eight percent, which corresponds to an improvement of 1.3 percentage points. The enhancement to price simple interlines further reduced the share gap from eight percent to six percent, an improvement of about 0.7 percent. The total impact of activating online triangle and simple interline searches was to cut the share gap by 55 percent with a two percent increase in booking share. Travelocity gained approximately 250,000 additional air bookings in the fourth quarter of 2005, worth $1.4 million, and we projected an increase of 1.2 million additional air-passenger bookings in 2006.

Given that Travelocity’s annual earnings increased by approximately $3.4 million per share point, the total benefit was $6.8 million per year.

Summary of Models and Benefits
In 2002, Travelocity was ill prepared for the changes taking place in its industry. Like many Internet companies at the time, Travelocity had prospered on growth. It recognized that it needed to change and adopt a more sophisticated business model. It more than doubled its annual revenues and regained lost share in the marketplace. Decision-support modeling to understand customer behavior, network planning, display, pricing, and marketing played an important role in this dramatic turn around (Table 4).

Additional benefits are associated with the incremental air bookings due to marketing modeling and LFS improvements. Customers shopping for airline tickets often purchase additional travel components (hotel and car) in the same session. This additional revenue is called the halo effect. Travelocity has measured the value of additional hotel and car revenues to be about 15 percent beyond the air bookings.

Beyond Travelocity
Based on its success in the US domestic market, Travelocity is expanding internationally. As it extends its efficient business practices, we expect the benefits to grow as well. For example, after Travelocity acquired

<table>
<thead>
<tr>
<th>Business area</th>
<th>Application</th>
<th>2002 ($)</th>
<th>2003 ($)</th>
<th>2004 ($)</th>
<th>2005 ($)</th>
<th>2006 (est) ($)</th>
<th>Total ($)</th>
</tr>
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<tr>
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<td>Conversion model</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>5.3</td>
<td>3.4</td>
<td>4.5</td>
<td>6.4</td>
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<tr>
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<td></td>
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</tr>
<tr>
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<td></td>
<td>8.2</td>
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<tr>
<td>Halo</td>
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<td>2.3</td>
<td>3.9</td>
<td></td>
<td></td>
<td>6.5</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>6.7</td>
<td>8.8</td>
<td>9.2</td>
<td>29.3</td>
<td>43.6</td>
<td>97.6</td>
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<tr>
<td>Revenue (millions)</td>
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<td>394.5</td>
<td>502.5</td>
<td>829.9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Profit (adjusted, millions)</td>
<td></td>
<td>(105.4)</td>
<td>(100.3)</td>
<td>12.6</td>
<td>26.6</td>
<td>110–120</td>
<td></td>
</tr>
</tbody>
</table>

Table 4: The enterprise network model has provided Travelocity with steadily increasing benefits since 2002. The total quantifiable benefits of the enterprise network model have grown from $6 million in 2002 to over $43 million per year in 2006. We expect the cumulative quantifiable benefits since 2002 to reach nearly $97 million in 2006.
LastMinute.com (one of the largest online travel agencies in Europe) in 2005, one of our new subsidiaries, Holiday Auto, asked for display and pricing assistance. We estimated that a simplified version of the enterprise network model would improve its earnings by approximately five margin points. We expect to implement this model in 2006 and apply the ENM to LastMinute.com’s main site.

Travelocity is one of 50,000 travel agencies connected to Sabre, representing six percent of the total sales volume of the larger Sabre business. Following the deregulation of the global distribution system marketplace, Sabre is also making a transition to become a travel retailer. What we have learned in terms of data and modeling to support Travelocity’s transformation is applicable to this larger business. For example, the changes we made to Travelocity’s low-fare-search algorithms immediately benefit all travel agencies that use Sabre.

The approaches and models we developed for Travelocity are applicable to any online retailer connecting suppliers and customers. The travel and transportation industry has led this development (Smith et al. 2001), but business efficiency can be improved throughout the online marketplace (Rao and Smith 2006).

In our work with Travelocity, we were consistently successful in a very dynamic environment. We started with a general direction and access to underutilized data. We developed a repeatable improvement process that involved understanding business issues, using data to support modeling, making decisions based on predicted benefits, and following up by monitoring and adjusting our methods.

Appendix. Demand Optimizer Model Formulation

The object of the demand optimizer is to determine how to influence ticket sales via service fees and merchandising efforts such that Travelocity’s air revenue is maximized. To simplify notation, we will discuss the model formulation for only one booking and travel period.

The demand optimizer contains three groups of decision variables: shift, market growth, and service fee variables. The shift and growth variables represent the combined impact of potential merchandising efforts on ticket sales. In particular, the shift variable, \( shift_{a,m} \), represents the number of ticket sales shifted to or away from carrier \( a \) in market \( m \). The growth variable, \( growth_{m} \), represents the change in total ticket sales in market \( m \). The shift and growth variables are constrained by user-defined estimates of the effectiveness of merchandising efforts.

The demand optimizers service fee variables \( (svcFee_{a,m}) \) represent the service fee that is charged for a ticket sale on airline \( a \) in market \( m \). In the demand optimizer model used at Travelocity, the impact of service fees on ticket sales is modeled explicitly using piecewise-linear functions. The parameters of these functions are computed via scenario analysis using the sales simulator. For simplicity of notation, we use here the transfer functions \( \Phi_{a,oa,m}(f) \). We let \( \Phi_{a,oa,m}(svcFee_{a,oa,m}) \) denote the change in ticket sales for airline \( a \) in market \( m \) given the service fee for airline \( oa \).

Before we state the model, we will introduce our notation and the remaining inputs to the demand optimizer model. A key input to the demand optimizer is the set of ticket-sales forecasts on the airline-market level \( (tixa_{a,m}) \). These forecasts are generated by the forecasting module.

A set of user-generated inputs defines deal parameters, commissions, and the bounds on Travelocity’s ability to influence demand:

\[
\begin{align*}
\text{comBase}_{a,m} & \quad \text{Base commission received for a ticket sale on airline } a \text{ in market } m. \\
r_{d,l} & \quad \text{Per ticket incentive commission paid under deal } d \text{ when level } l \text{ is reached.} \\
\text{shiftMin}_{a,m} & \quad \text{Upper bound on the number of ticket sales Travelocity can shift away from airline } a \text{ to another airline in market } m. \\
\text{shiftMax}_{a,m} & \quad \text{Upper bound on the number of ticket sales Travelocity can shift toward airline } a \text{ from another airline in market } m. \\
\text{growthMin}_{m} & \quad \text{Upper bound on the total number of ticket sales Travelocity can decrease in market } m. \\
\text{growthMax}_{m} & \quad \text{Upper bound on the total number of ticket sales Travelocity can increase in market } m. \\
tixa_{a,m} & \quad \text{Number of tickets already sold on airline } a \text{ in market } m. \\
\text{share}_{a,m} & \quad \text{Expected market share of airline } a \text{ in market } m.
\end{align*}
\]
When formulating the model, we will use $A$ to denote the set of all airlines, $M$ the set of all markets, $D$ the set of all incentive deals, and $L(d)$ the set of all performance levels of incentive deal $d$.

The objective function of the demand optimizer model has three components: airline- and market-specific base commissions, performance-deal-specific incentives, and airline- and market-specific service fees:

$$
\max \sum_{a \in A} \sum_{m \in M} (tix_{a,m} + \Delta tix_{a,m}) \text{comBase}_{a,m} + \sum_{d \in D} \text{comIncent}_d \nonumber
$$

$$
\quad + \sum_{a \in A} \sum_{m \in M} (tix_{a,m} + \Delta tix_{a,m}) \text{svcFee}_{a,m}. \quad (1)
$$

The first two sets of constraints enforce the bounds on the shift- and market-growth variables:

$$
\begin{align*}
\text{shiftMin}_{a,m} & \leq \text{shift}_{a,m} \leq \text{shiftMax}_{a,m} & \forall a \in A, m \in M, \quad (2) \\
\text{growthMin}_m & \leq \text{growth}_m \leq \text{growthMax}_m & \forall m \in M. \quad (3)
\end{align*}
$$

The next set of constraints is concerned with the change in ticket sales for airline $a$ in market $m$ due to sales shift to/from airline $a$ in market $m$, and growth of market $m$. We will use auxiliary variables $\Delta_{a,m}$ to express this change:

$$
\Delta_{a,m} = \text{shift}_{a,m} + \text{growth}_m \text{share}_{a,m} + \sum_{o \in A, o \neq a} \Phi_{a,oa,m}(\text{svcFee}_{oa,m}) \quad \forall a \in A, m \in M. \quad (4)
$$

The last term in (4) captures the impact that changing the service fee of one carrier has on ticket sales of all carriers in the market. We model share shifts, though, as decisions that affect only one carrier’s ticket sales. We ignore interdependencies of share shifts. In reality, however, changing one carrier’s market share affects the share and, in turn, the ticket sales of competing carriers. We accounted for these affects in an additional set of constraints that determine the net change in ticket sales. We use auxiliary variables $\Delta tix_{a,m}$ to express the change in ticket sales. The underlying assumption is that second-order effects are a function of current market shares:

$$
\Delta tix_{a,m} = \Delta_{a,m} - \text{share}_{a,m} \sum_{o \in A, o \neq a} \frac{\text{shift}_{oa,m}}{1 - \text{share}_{oa,m}} \quad \forall m \in M, a \in A. \quad (5)
$$

Finally, two sets of constraints capture the relationship between ticket sales, incentive targets and incentive pay. In particular, for each incentive deal, one set of constraints links ticket sales to performance-level indicators, forcing the indicators of all unachieved performance levels to zero. These constraints are deal-structure specific and are not shown here. The second set of constraints establishes an upper bound on incentive pay based on the highest achieved performance level. We use two more sets of auxiliary variables to formulate these constraints. The binary variable $\delta_{d,k}$ equals one if and only if performance level $l$ of deal $d$ is reached. The variable comIncent$_d$ represents the incentive revenue collected from incentive deal $d$:

$$
\text{comIncent}_d \leq \text{bigM} \sum_{k \in L(d), k=1} \delta_{d,k} + r_{d,l} \sum_{m \in M} (tix_{a(d),m} + \Delta tix_{a(d),m} + \text{toDate}_{a(d),m}) \nonumber
$$

$$
\quad \forall d \in D, l \in L(d), \quad (6)
$$

where bigM denotes a large number and $a(d)$ is the airline with which deal $d$ exists. The large number bigM de-activates the constraint for level $l$ if a higher performance level has been reached.

References


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At the Edelman competition presentation, Michelle Peluso, president of Travelocity commented: “Travelocity has come a long way since 2002. Our success has been based on the introduction of great products, a wonderful team, terrific branding, advertising campaigns, and more effective use of marketing mix. But also at the heart of it is the knowledge we’ve gained from the operations research team. Insights from data and customer models transformed the way we make decisions at Travelocity by ensuring that we have the right deals in front of the right customers at the right time. Understanding what customers want and using that insight to drive better decisions is at the heart of how we have succeeded. Every time we implemented a new capability, we quantified the impacts. As the team prepared the estimates for the Edelman competition, if anything I think the impact estimates are conservative. This has not been one project or two projects; this is a way of doing business; it is a way of transforming who Travelocity is versus our competitors. I think we will see benefits long into the future.”