**Powering retailers’ digitization through analytics and automation**

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Powering Retailers’ Digitization Through Analytics and Automation

By David Simchi-Levi¹ and Michelle Xiao Wu²

Abstract

Retailers face significant pressure to improve revenue, margins and market share by applying price optimization models. These are mathematical models that calculate how demand varies at different price levels, then combine that data with information on costs and inventory levels to recommend prices that will improve revenue and profits. These models have been around for a while-so what is different now? We have identified three important changes:

- **Data:** availability of internal and external real time data such as traffic to a website, consumers making buy/no buy decisions and competitor pricing strategies;

- **Analytics:** advances in machine learning and ease of access (R, Python) have enabled the development of systems that learn on the fly about consumer behavior and preferences and generate effective estimates of demand-price relationships;

- **Automation:** increase in computing speed enables real-time optimization of prices of hundreds of competing products sold by the same retailer.

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We take advantage of these new opportunities by showing how they were applied at Boston based flash sales retailer Rue La La, online market maker Groupon, and the largest online retailer in Latin America, B2W Digital (B2W).

While all these examples are of on-line businesses which have readily available data and can change prices dynamically, we have also implemented similar methods for brick-and-mortar retailed in applications such as promotional pricing, new product introduction, and assortment optimization with similar business impacts. Thus, beyond applications to price optimizations, these new trends enable companies to revolutionize their business from procurement to supply chain all the way to revenue management.

**Introduction**

Never have retailers been in such a complex and competitive environment. Multi-channel distribution involving brick-and-mortar stores and online selling, rising and changing customer expectations, short selling seasons and many products competing in the same markets are just some of the challenges faced by retailers. These companies are already lean so there is little room to cut cost. Therefore, with small and declining margins, retailers have an opportunity to increase revenue and improve margins through more technologically advanced price optimization.

Unfortunately, price optimization can be extremely complex; for review of pricing models and challenges see [Özer, Ö., Ozer, O. and Phillips, R. eds. (2012), Talluri, K.T. and Van Ryzin, G.J. (2006)]. It requires understanding consumer valuations--how much
consumers value different products—and it demands analyzing vast quantities of data as well as understanding competitors’ behavior. The data itself may also be a problem. Indeed, to optimize price, one needs information about demand-curves, that is, the relationship between demand and price. But the available data typically represents sales information and when inventory is limited, quantity sold may underestimate customer demand because of lost sales during stock-out time. Finally, for certain products, in particular high-end fashion products, demand-price relationship is not necessarily linear—price is an indication of quality and hence, within a certain range, the higher the price, the higher the demand.

Price optimization can be very risky! Indeed, for many online sellers, frequently changing or experimenting with price is not appropriate because of the negative customer reaction or fear of confusing the market. At the same time, increasing a price may increase revenue and margins but can decrease market share.

So, if frequently changing and experimenting with price is not appropriate, what is a retailer to do to maximize revenue, margins and market share? Is it even possible to optimize price in a way that simultaneously increases these three objectives? And, how does one even measure the impact of a price change on market share? These are the questions that our recent collaborators--Boston based flash sales retailer Rue La La, online market maker Groupon, and the largest online retailer in Latin America, B2W Digital (B2W for short)--have all focused on.
To address these challenges, we developed a new methodology that combines three different techniques: Forecasting, Learning, and Price Optimization. Forecasting is about generating an initial demand-price relationship for a product that was never sold before. Here we applied machine learning technologies such as Regression Trees or Random Forest in order to generate the initial forecast. Learning is about observing customers making buy/no-buy decisions and using that information to update the demand-price curve. Finally, price optimization is about the simultaneous selection of price for all competing products offered by the retailer.

Importantly, not every company needs, or is able to apply, the three building blocks described above. For example, in the Rue La La price project, we focused on Demand forecast and Price optimization since the company did not want to change the price during a selling event. For Groupon, we quickly realized that it is difficult to generate a reliable demand forecast so we focused on learning in real time about the demand-price curve, and once we learnt enough, we switched to price optimization. Finally, in the case of B2W, we combined all the three building blocks, namely, forecasting, learning and price optimization.

To explain our methodology, we start by recounting the Rue La La story that will highlight the innovation and impact of our demand forecasting and price optimization method. We then follow with the Groupon story, highlighting the challenge of generating effective forecasts and the impact of learning and optimization. We conclude with the B2W story that illustrates how all the three building blocks can be combined.
Forecast and Price Optimization at Rue La La

Rue La La is in the online fashion sample sales industry, where they offer extremely limited-time discounts (“flash sales”) on designer apparel and accessories. Upon visiting Rue La La's website, the customer sees several “events”, each representing a collection of for-sale products (“styles”) that are similar in some way. At the bottom of each event, there is a countdown timer informing the customer of the time remaining until the event is no longer available; events typically last between 1-4 days. Flash sales businesses like Rue La La aim to create a feeling of urgency and scarcity of products by offering great deals but for limited time and with limited inventory.

One of Rue La La's main challenges is pricing and predicting demand for items that it has never sold before (“first exposure” items), which account for the majority of sales. Figure 1 shows a histogram of the sell-through (percent of inventory sold) distribution for first exposure items in Rue La La's top 5 departments. For example, 51% of first exposure items in Department 1 sell out before the end of the event, and 10% sell less than 25% of their inventory.

The observation that a large percent of first exposure items sell out before the sales period is over, suggests that it may be possible to raise prices on these items while still achieving high sell-through; on the other hand, many first exposure items sell less than half of their inventory by the end of the sales period, suggesting that the price may have been too high. This use of descriptive analytics motivated the development of a pricing
decision support tool, allowing Rue La La to take advantage of available data in order to maximize revenue from first exposure sales.

![1st Exposure Sell-Through Distribution](image)

Figure 1: First Exposure Sell-Through Distribution by Department

Because Rue La La is not interested in changing the price during the first exposure event, learning from customer on-line behavior was not an option. Hence, our approach was two-fold and begins with developing a demand prediction model for first exposure styles; we then used this demand prediction data as input into a price optimization model to maximize revenue. The two biggest challenges faced when building our demand prediction model include estimating lost sales due to stock outs, and predicting demand for styles that had no historical sales data.

To address the first challenge, we split historical sales data into two groups: Group one includes all item-event combinations that did not stock out while Group two includes
those item-event combination that did stock out. We use sales data from items that did not sell out to estimate lost sales for items that did sell out.

For this purpose, for each event-item combination in either group, we calculated the percent of sales that occur in every hour of the event. This gives rise to an empirical distribution, or demand curve, of the proportion of sales that occur in the first, say, k hours of an event. We then aggregated all these demand curves in Group one into just a few distinct and interpretable curves by applying a clustering technique that looks for all demand curves with similar structure, and generated four different curves, see Figure 2.

As Figure 2 shows, the various event-item combinations of those items that did not stock out (Group one) can be described by a total of four curves: all events that start at 3PM; at 8PM; Monday to Friday events that start at 11am; and weekend events that start at 11am. Thus, for every event-item combination that stock-out, and hence belongs to Group two, we identify which curve (out of the four curves) is appropriate based on start time. Since we know the time this item stocked out, we can immediately estimate total demand for this product based on the corresponding demand curves from Group one. For instance, suppose an item in Group two is associated with an event that started at 3PM and it stocked out after 10 hours. The curve in Figure 2 associated with 3PM indicates that sixty percent of total sales occur by the tenth hour. Thus, the total demand for this item is estimated as the initial inventory divided by 0.6.
Once we applied the clustering technique and generated estimated demand for items that stock out, we were ready to predict future demand. Regression trees, a machine learning technique, have proven to be the best predictors of demand. To the best of our knowledge, this is the first application of regression trees used for demand prediction.

Regression trees are a collection of rules that when followed, will end up with a prediction. Figure 3 provides an example. We start at the top; if price for the product is less than 100, we move to the left, otherwise you traverse the tree by moving to the right. Suppose we are considering a price less than 100, so we move to the left. Once we move to the left, the next rule involves comparing the price of the product to the average price of all competing products sold by Rue La. If the ratio between the two is less than 0.8, we move again to the left and the regression tree predicts that in this case demand is 50 units.
We believe that there are two reasons for the effectiveness of regression trees. The first is that it can successfully partition all items sold in the past and only use the relevant one to predict demand for the current (new) item. The second is that it allows for a non-monotonic price demand relationship, a characteristic not shared by traditional linear regression techniques, but critical for many fashion and high-end products where price can be considered a signal of quality.

![Figure 3: Illustration of a Regression Tree](image)

We then formulated a price optimization model to maximize revenue from first exposure styles, using demand predictions from the regression trees as input. In this case, the biggest challenge we face is that each style’s demand depends on the price of competing styles, which restricts us from solving a price optimization problem individually for each style and leads to an exponential number of variables in the price optimization problem. Furthermore, the unique structure of regression trees makes this problem particularly difficult to solve.
We developed a novel reformulation of the price optimization problem and created an efficient algorithm that allows Rue La La to optimize prices on a daily basis for the next day’s sales.

To implement our price optimization algorithm, we developed and implemented a fully-automated pricing decision support tool at Rue La La. It is run automatically every day, providing price recommendations to merchants for events starting the next day. The entire pricing decision support tool is depicted in the architecture diagram in Figure 4.
To estimate the tool’s impact, we developed and conducted a field experiment on approximately 6,000 styles from mid-January through May 2014 to address the following two questions of particular interest to Rue La La: (i) would implementing the tool’s recommended price increases cause a decrease in demand, and (ii) what impact would the price increases have on revenue?

For our field experiment, we used statistical methods to test the hypothesis that raising prices according to the pricing decision support tool’s recommendations has no negative impact on demand. We performed this test on styles in different price ranges, and the results suggest that raising prices only negatively impacts demand for very low-priced styles (price < ~$50). As a result, for product in this range we added a cap on the increase in price (no more than $5). Finally, we quantified the financial impact of our tool for styles in each price range; the overall impact was approximately a 10% increase in revenue.

**Learning and Price Optimization at Groupon**

Groupon, a large e-commerce marketplace for daily deals, offers subscribed customers discount deals from local merchants. By the second quarter of 2015, Groupon served more than 500 cities worldwide, had nearly 49 million active customers and featured more than 510,000 active deals globally.

As an example, Figure 5 shows a local restaurant deal on Groupon's website. The deal can be purchased through Groupon at $17 and redeemed at the local restaurant for $30.
The amount paid by a customer ($17) is called “booking”. The booking is then split between Groupon and the local merchant, for instance, Groupon keeps $7 while the local merchant receives $10.

Figure 5: Groupon online daily deals

The company launches thousands of new deals every day, and these deals have a short lifecycle, ranging from several days to several weeks. The combination of the huge product portfolio and short lifecycle implies that demand prediction is quite challenging. The problem of course is that Groupon needs an effective demand prediction model to optimize price, but unfortunately it is impossible to develop such a forecast.
To address this challenge, we generate multiple forecasts at the time a product is launched on the company web-site. A forecast, as in the case of Rue La La, is a demand-price relationship specifying predicted demand for every price within a given range. The idea behind our approach was to generate multiple demand functions, such that the true demand-price relationship is approximated well by one of these demand functions. Of course, when the selling process starts, we had no idea which demand function, among the multiple forecasts, is the best to capture consumer behavior.

For this purpose we applied a two-step process: Learning and Optimization. We split the product life cycle, the time the product is sold on the website, into two parts, the first portion is learning while the second is the price optimization. When the product is introduced on Groupon’s website, we initially apply a learning price and observe customers making buy/no-buy decisions. At the end of the learning period, we know how much we sold and therefore we can identify the demand prediction that has the closest demand prediction to this level of sales at the learning price used by Groupon. This is the final demand-price function we will use and we optimize price based on this demand-price function during the optimization period.

The tradeoffs in our algorithm are clear. If we learn for a long time (long learning period), then we will have a good understanding of the true demand function but there is little time remaining for the optimization. By contrast, if we learn just for a short period of time, we will have an approximate understanding of customer demand but we can use the final, optimized price, for a long period of time.
When implementing our approach for the first time, we initially generated for every new deal around ten demand functions. Very quickly we realized that this is not enough and in the final implementation, we generated for every new deal around 100 demand functions. These demand functions were associated with the new deal category, the city or region where the deal is sold, the price range and discount considered for the deal, etc.

In the final implementation, Groupon imposed a few business constraints on our learning and optimization approach. First, the learning price is negotiated between Groupon and the local merchant and cannot be determined by our algorithm. Second, Groupon only allowed us to decrease price at the end of the learning period in the range of 5% to 30%. That is, if the algorithm recommends a price increase or a less than 5% price decrease, than the price is not changed. Similarly, if the algorithm recommends a price decrease greater than 30%, then the decrease is capped at 30%. Finally, the local merchant receives a fixed share. For example, in the restaurant deal of Figure 5, before the price decrease the deal is sold for $17 and the local merchant receives $10. If at the end of the learning period, our algorithm recommends to decrease the price to $15, the local merchant still receives $10 while Groupon collects $5 instead of $7. This implies, that local merchants always benefit from the price decrease, since they see the same payment for every deal sold while increasing traffic to their products due to the price decrease. The challenge is for Groupon. On the one hand, revenue per deal goes down. On the other hand, they may sell more deals. The question was what the net effect is.
The field experiment included 1,295 deals that spanned five product categories: Beauty, Food & Drink, Activities, Services, and Shopping. We focused on two performance measurements. One was the total amount of money paid by customers to Groupon, referred to as bookings, which is directly related to Groupon's market share; the other was the portion of money that Groupon keeps after paying local merchants, referred to as revenue. For each product category, we compared the average bookings and revenue before and after a price change. Since the learning price is determined in the same way as in fixed pricing, the bookings and revenue before the price change represent the performance for a fixed pricing strategy. Note that if a deal is tested using our pricing algorithm but the algorithm does not recommend a price decrease, then this deal is not included in the 1,295 selected deals.

Figure 6 shows the average increase in bookings and revenue after price changes by category. The numbers in parentheses are the quantity of deals tested in each category. Among the five categories, Beauty, Food & Drink, and Shopping have significant revenue increase, Services category has almost no revenue change but significant bookings increase, and the Activities category has a decrease in revenue. Overall, bookings increased by 116%, and revenue increased by 21.7%.

Further analysis of the results from the field experiment showed that reducing price has a much bigger impact on deals that have fewer bookings per day. For deals with bookings per day less than the median (across all product categories), the average increase in revenue was 116%, while the increase was only 14% for deals with bookings per day
more than the median. This explains the big increase in bookings and revenue for the Shopping category, because the average daily bookings of the Shopping category were only around one tenth of the average daily bookings in the Food & Drink category.

Our pricing algorithm performed poorly for the Activities category, despite the fact that this category has almost the same level of average daily bookings as the Beauty category. We suspect that some information of customer demand for Activities is not included in our demand model. For example, it might be that the weekend/holiday effect is much more significant for this category than we estimated, or perhaps the holiday effect happens a few days before the actual holiday. Further work is needed to improve the demand prediction method for the Activities category.

Figure 6: Live Experiment: Impact by Deal Category
**Forecasting, Learning and Price Optimization at B2W**

B2W Digital, the largest online retailer in Latin America, was established in 1999 and competes with companies such as Amazon and Walmart. The company has four on-line brands Americans.com, Submarino, Shoptime and SouBarato which offer more than 40 categories of products. The dynamic pricing algorithms described in this section were implemented in all brands with the exception of Shoptime which is a TV channel.

The rich portfolio of products offered by B2W, the accessible historical sales data for these products, and the ability to change price multiple times during a day provided us with a unique opportunity to combine forecasting, learning and optimization. In the first step, we generate a forecast for every product that takes into account internal and external data. Internal data includes traffic to the site, price, discounts, advertisement spending, competing products offered on the B2W web-site and their prices. External data includes for example competitor pricing, competitor’s advertisement campaign, and weather conditions. As in the case of Rue La La, regression trees—in fact, a more sophisticated version called Random Forest—turned out to be the best in predicting demand–price relationships.

The second step involves learning. Every few hours we observe changes in traffic to the web-site, demand to B2W products or competitor behavior and we update the regression tree to better represent current market conditions. Finally, we apply price optimization across all products offered by B2W that compete against each other in the same market.
In August of 2016, B2W started the live implementation. The tool runs a few times a day, every time updating the demand forecast by learning from the last few hours’ change in conditions—traffic to the B2W web-site, competitor prices and B2W sales. The new forecast, generated through the learning process is used by the optimization model. In this implementation, there is no manual intervention; all prices are pushed directly to the web-site. During the implementation, B2W emphasized three different performance measures: revenue, margins and market share estimated by number of units sold.

To understand the impact of the dynamic pricing strategy on the three performance measures, we focused on three product categories: Low Priced Products; Fast Selling Products; and Premium Products. Each product category was split into two groups, the control where B2W merchants applied their traditional pricing strategies and the treatment where the new technology pushed prices directly to B2W web-site. Figure 7 represents the impact of the dynamic pricing algorithm on two products categories: low price and fast selling products. Green bars represent the performance of the treatment group while blue is associated with the control.
As you can see, the impact is quite impressive. For low priced products, revenue increased by 66%, profit by 44% and number of unit sold, which is a proxy for market share, increased by 141%. The results for fast selling products are not as impressive, but still quite strong: increased revenue by 17%, profit by 30% and number of unit sold by 30%.

Premium products provided an opportunity to understand the importance of price optimization. Indeed, without applying price optimization, revenue in the treatment group decreased relative to the control by 264%, profit by 416%, and number of units by 216%. However, with the optimization engine in place revenue in the treatment group increased by 471% relative to the control; profit increased by 366% and the number of unit sold increased by 391%.

At the end of the field study which ran for a few months, B2W reported that the new technology not only improved revenue, profit and market share but also had an impact on the breadth of product sold, that is, B2W was selling more unique products in the treatment group than in the control group. This helped position B2W Digital in the market as the “better price company every day, for every product.”

Key to Success
The technology developed for price optimization, or for that matter any other big data analytics initiative, cannot stand on its own; it needs to be complemented by appropriate change management steps where the data analytics is embedded as part of the day-to-day management process. The three stories described in this article highlight organizations that were able to successfully integrate analytics and managerial processes and become truly data driven organizations. How was this accomplished?

First, they use data from external sources, such as brand reputation or competitors’ prices, to complement internal data. Second, these organizations emphasize data quality and break silos between different functional areas so that data is shared across the organization. Third, they attract data analytics specialists who can implement this type of technology. And finally, they overcome internal resistance by recognizing that the technology is not going to replace the merchandisers or sales executives. Indeed, there are many detailed and intangible considerations such as consumer preference, product characteristics or market conditions that these executives understand but the technology cannot capture. Therefore, integrating business processes and the price optimization technology to allow the experts to weigh in is an important part of becoming a truly data driven company.

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References:


