OMNI-CHANNEL MARKDOWN OPTIMIZATION

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The commercialization of this work is a result of the combined efforts that includes the following team members from the IBM Commerce business unit: Saibal Bhattacharya, Irina Fedulova, Vitaly Grechko, Nikolay Murzin, Manjunath Pandit, Emily Port, Erich Schellhas, Maloney Whitfield, Oleg Sidorkin, Mahesh Virupakshaiah, Jin Jing Xie, Emrah Zarifoglu and Pavel Zelinsky. This list includes the data scientists, product managers and client executives. We sincerely acknowledge the Omni-channel Retailer who wishes to remain anonymous and more specifically, their pricing team, who provided the key business motivation and insights that helped in shaping the solution design.

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1. Executive Summary

Through a partnership with IBM Commerce, a leading provider of merchandising solutions, we engaged with a major U.S. retailer to address the challenges it faced in its switch to omnichannel operations, and together developed the next generation omnichannel markdown optimization (MDO) system. The retailer operates more than 1,000 stores and an online store. Store inventory is extensively used to fulfill online orders via ship-from-store (SFS) fulfillment option. Our team developed a data-driven omnichannel system (demand forecast engine, price optimization engine) that:

1. Models demand substitution between the online and store channels,
2. Jointly optimizes omnichannel prices (OCP) and cross-channel fulfillment inventories (X),
3. Handles various business constraints (e.g., price bounds, minimum time between price changes),

which we refer to as the OCPX system. A proprietary implementation of OCPX is now commercially available as part of the IBM Commerce Markdown Price Solution. The retailer has been gradually transitioning its clearance pricing to OCPX analytics in a live pilot. A causal model analysis on the live pilot data shows a 12% increase in clearance period revenue with OCPX analytics. Gains from OCPX arise inventory rebalancing using omnichannel prices (more SFS inventories from stores with low sell-through rates) and through better management of channel demands.

2. Challenges in Omnichannel Revenue Management

Omnichannel integration is a recent trend in the retail industry, which aims to create a seamless customer shopping experience through an alignment of the retailer’s online channel and the brick-and-mortar channel. This makes it convenient for customers to compare online and store prices, to purchase from any channel, and to receive the product via several fulfillment options. Enabling these capabilities allows the retailer to be competitive in a fast growing online market. Amazon.com, the largest U.S. e-commerce retailer, is poised to benefit from online sales growth due to its efficiency in fulfilling online orders from its multiple e-fulfillment centers (EFCs). In contrast, primarily brick-and-mortar retailers only have a few EFCs due to the significant fixed cost of each. Hence, an operational benefit from omnichannel integration is to enable the use of the brick-and-mortar store network to fulfill online sales via ship-from-store (SFS) fulfillment or buy-online-pickup-in-store (BOPS).

Omnichannel integration introduces challenges for markdown optimization, specifically to retailers with MDO systems based on traditional models. Traditional MDO models set markdowns separately for each store with the objective of clearing off remaining store inventory with store customers only. With SFS fulfillment, the store inventory is also opened up to online customers. But since a standalone order management system (OMS) typically determines store fulfillment, the legacy pricing system cannot set appropriate markdowns since it does not know the true remaining inventory for store sales. Another challenge from omnichannel is due to the more accessible price information, which could introduce demand substitution between channels (e.g., showrooming). Channel substitution is ignored in the traditional systems which assume price only affects demand in the same channel. Despite these new challenges, many omnichannel retailers (including our partner retailer)
utilize legacy MDO systems that do not account for any channel interdependencies.

In the presence of cross-channel effects, using legacy MDO systems can have negative consequences which we demonstrate with an example. Fig. 1 shows the weekly channel prices (online price and average store price) and weekly channel sales of a Tablet SKU marked for clearance on Week 40. On Week 40, the legacy software sets steep initial markdowns in the brick-and-mortar stores to clear all store inventory over the next 12 weeks from store customers (see topmost panel). However, not all store inventory is at risk of becoming unsold since all online sales are SFS fulfilled during the clearance period (see middle panel). Because of the steep store markdowns, after an initial sales spike, total brick sales steadily decline due to an increasing number of stores stocking out (see bottom panel). In contrast to the steep brick markdowns, the legacy system initially sets the regular price for the online channel (since EFC inventory is depleted by Week 40, hence the system assumes there is no inventory left for online sales). However, due to the substitution effect, setting the online price significantly higher than brick price causes channel cannibalization. Merchandise managers would override the price outputs from the system to reduce this difference by making ad-hoc adjustments to the system inputs. A common adjustment used to set the online price (also applied to the Tablet example of Fig. 1) is to inject artificial inventory to the EFC. In discussions with merchandise managers, this manual adjustment process was revealed to be unmanageable and time consuming, and the bigger concern was the steep brick markdowns resulting in systemwide margin erosion.

3. Our Solution Approach

In collaboration with the partner retailer (a major retailer with annual sales of more than $40 Billion and operating more than 1,000 stores), we developed a data-driven omnichannel markdown optimization system. We next describe the phases in our solution approach.

First, we worked with all stakeholders to define the business problem, select the product categories to be analyzed (Notebooks, Tablets, and Tablet Accessories), and process the data (transaction log data, inventory data, holiday index data, and price data of 18 online competitors).

Second, we developed an omnichannel network demand model for location-level demand [J1,P1]. Customer locations are represented by a discrete set of nodes, which are determined by geospatially clustering the market into “zones” (see Fig. 2, where each node represents a zone). We model a zone customer’s channel choice probability (online, store or no-purchase) with a multinomial logit (MNL) model. Zone-tagged channel transaction data (and other zone-tagged causals) are used estimate preferences. Compared with demand models typically used in retail pricing, our demand model is able to include cross-channel causals aside from the conventional same-channel causals. Our demand model also incorporates (i) the product lifecycle effect using shape parameters of a beta distribution, and (ii) competitor effects using price data of multiple competitors as covariates.

To estimate the MNL models without no-purchase data, we develop a novel integrated mixed-integer programming (MIP) approach that jointly estimates prediction parameters associated with market size and the market share from censored sales data [J3, P3]. Endogenous imputations are per-
formed in the MIP to estimate the probabilities of the unobserved lost sales. This procedure enables us to recover proven, (near-) global optimal parameter values. This method has been extensively tested in a variety of different industrial settings, including omnichannel retailing, and other public data sets. We enhanced the MIP with features such as regularization using lasso and ridge penalties and sign constraints on price coefficients to enable an automated demand estimation environment.

Third, we developed an **omnichannel network markdown optimization model** (referred to as OCPX) that maximizes chainwide revenue (clearance sales dollars plus salvage value of unsold items) by jointly optimizing markdowns in the retail chain [J2, P4]. In clearance pricing, the optimal markdown (online or in a store) depends on the remaining *available* inventory. A store inventory is “available” for store sales if it is not used for SFS fulfillment (otherwise, it is “available” for online sales). A major modeling challenge is that SFS fulfillment is determined by a standalone OMS that does fulfillment satisfying operational requirements. To address this, we introduce *inventory partition* variables to the model in order to approximate the future use of omnichannel inventories. These variables ration the store inventory to be used for online fulfillment, similar to booking limits in capacity control. In capacity control problems, the booking limits are met by accepting or rejecting customers. In contrast, the inventory partitions are met by directly influencing omnichannel demand through price management. Fig. 3 is an illustration which highlights the benefits of OCPX over the legacy system for clearance pricing. The OCPX model can handle various business constraints (e.g., price bounds, decreasing prices, minimum time between markdowns, same online price for all zones, maximum markdown budget) – an important requirement for any pricing system.

A key feature of OCPX is that shared omnichannel inventory and zone-coupling price constraints require a network optimization model encompassing both channels and all zones, in contrast to legacy MDO models which optimize prices at one channel or store location at a time. For example, a legacy MDO system would solve 1000+ separate clearance pricing model (one for each retail store and one monolithic online store), whereas OCPX solves a single integrated price optimization model across all stores (problem instances had up to 10K binary variables, 50K flow variables and 100K constraints). The challenge in solving OCPX is that it is large-scale nonlinear and non-convex. However, we are able to exactly reformulate the OCPX model as a MIP if the feasible price set is discrete – not a restrictive assumption since prices are typically required to satisfy fixed discount levels (e.g., 20%, 30%, 40%) or have magic number endings (e.g. ending with $0.99). We reformulate OCPX by: (i) introducing binary variables corresponding to each feasible price, (ii) “lifting” the nonlinear model to a higher-dimensional MIP, then (iii) showing that the MIP is a tight upper bound to OCPX by constructing feasible solutions to each with the same objective value. The MIP formulation of OCPX is computationally tractable and can be solved efficiently using commercial optimization solvers like CPLEX (in a few seconds in most instances), making OCPX suitable for a production environment.

Fourth, we conducted a business value assessment with the data provided by the retailer to estimate the projected revenue impact of an OCPX system (demand forecasting model and OCPX...
optimization model) on representative product categories. Their feedback was overwhelming positive and they immediately requested for commercialization of an OCPX-enabled system. To productize the new OCPX solution, we collaborated with the IBM Commerce team who developed the necessary IT infrastructure, data processing, analytics integration, and user interface. As an intermediate step before fully transitioning to the OCPX system, additional tests were performed that used the OCPX partitions in the incumbent system to gauge benefits by SKU (with and without OCPX) using the incumbent forecasting engine. This was a necessary step to gain support from the partner retailer’s pricing analysts and senior executives who were well-versed with the incumbent system. The successful results from the independent test convinced both IBM Commerce and the partner retailer of the benefits achievable by the OCPX system and led to the full-scale commercialization of the proprietary version of the solution, with the partner retailer as its pilot client. The solution is now commercially available as part of the IBM Commerce Markdown Price Solution and the capabilities of the solution were announced at the IBM Amplify 2016 conference [O2].

Finally, the retailer gradually transitioned the pricing of its clearance SKUs to OCPX analytics, starting in Q2 2016. We mention that a controlled field experiment to assess the clearance revenue improvement from OCPX could not be executed for several reasons:

1. Evaluation using close substitute SKUs is not possible, since not only should the matched SKUs have similar demand patterns, but the networkwide distribution of inventory at the start of the clearance period should also be identical,
2. Because a SKU is only in clearance for one season before being retired, we cannot apply pre-treatment (legacy) and post-treatment (OCPX) on the same SKU. Hence, estimating the causal effect through a Difference-in-Differences technique cannot be done.

Hence, we estimated the revenue improvement from OCPX using the pilot data through causal model analysis with appropriate pre-treatment predictors.

\section{Results and Impact}

Details of all results presented in this section can be found in [J2].

\subsection{Omnichannel Demand Forecasting}

We evaluated our omnichannel demand model by testing it for clearance demand prediction of 195 SKUs in the three product categories (Notebooks, Tablets, Tablet Accessories). The forecast accuracy was measured using the weighted mean absolute percentage error (WMAPE) of predicted out-of-sample weekly sales. Fig. 4 shows the zone-level predicted sales and actual sales for a sample SKU. The WMAPE at the category-level was 22%. We compared this with the forecast accuracy of a demand model without the cross-channel causals. The omnichannel demand model which includes cross-channel causals reduces WMAPE by 1.5 percentage points for zone-level store sales forecasts, and by 5 percentage points for zone-level online sales forecasts.

Average price elasticity values (Table 1) for the categories analyzed show (i) relatively high same-channel elasticities that are typical of clearance products, and (ii) significant cross-channel elasticities.
By including as covariates prices of multiple competitors, our estimation method is able to identify from sales and price data the most significant competitors to the retailer by SKU [P2]. We use the estimated competitor price elasticities to construct the retailer’s revenue-at-risk profile arising from competitor price changes in Fig. 5. The ability of the OCPX system to quantitatively identify and visualize competition risk has been a popular feature among retailers (see press release [O1]).

4.2. **Business value assessment results**

We report the results of the business value assessment presented to the partner retailer. Using the calibrated demand models for the 195 clearance SKUs, we solve the OCPX MIP model to determine optimal omnichannel clearance prices. We use the omnichannel demand models to project channel sales and clearance revenues of the OCPX prices. As a baseline, we compare the projections with the historical prices (legacy system output with possible manual adjustments), historical channel sales, and historical revenues. Table 2 shows for each category the average OCPX channel prices, and the projected impact on category-wide sales and clearance revenues. We make the following observations: (i) the retailer was setting steeper markdowns than optimal in brick-and-mortar stores, (ii) the OCPX online prices are lower than the historical online prices, resulting in a projected increase in online sales, and (iii) OCPX prices result in higher total sales (7% on average across all categories with more than 23% reduction in unsold inventory and more than 21% reduction in lost store sales).

While the cause for the increase in online sales activity is obvious, the increase in store sales for two of the categories is less obvious since OCPX store prices are higher. The root cause of this increase is the conversion of lost store sales into actual sales through: better demand management with omnichannel prices and by setting lower SFS partitions for stores that are likely to sell out. The combined effect of the optimal prices and fulfillment inventories yields an increase in the clearance revenue ranging between 6% and 12%. This translates to a combined projected annual increase of $12.5 million in the total revenue from the clearance pricing of the 195 SKUs alone.

The key observation in the independent testing was that the OCPX revenue gain varies by category and is positively correlated with the online SFS activity (see Fig. 6). The OCPX system results in 2% shallower brick markdowns on average due to inventory partitions.

4.3. **Revenue Impact**

Implementing the MDO system with OCPX analytics resulted in a **12% increase in the clearance revenue**. We estimated this through causal model analysis of the live pilot data. We obtained approximately one year of data from the IBM Commerce production system for a sample of SKUs across 34 categories, where each SKU either had the OCPX treatment or not. All SKUs had online presence, and had a markdown end date in Q1 2017. We selected SKUs where we observed the full clearance season and at least a partial regular season. For the average treatment SKU, the online sales share is 12.6% during the regular season and this nearly doubles to 24.1% during clearance season. In addition, nearly 98% of online sales during clearance season is fulfilled using SFS with approximately 20% of store inventory.
The dependent variable in the causal model is the log markdown revenue rate. Since we expect that gain in markdown revenue from OCPX is proportional to the online share, we interact the regular season online share with the treatment effect. We control for pre-treatment predictors: regular season online share, log regular season revenue rate, and the normalized initial clearance inventory. Table 3 shows the estimation results on two regression models, with and without channel-specific markdown depth, and note the consistent estimate for both. Based on the coefficient estimates, the difference $\alpha_3 - \alpha_4$ is the percentage markdown revenue change per online share due to OCPX. Using the treatment group’s average regular season online share (12.6%), we compute the average revenue improvement due to OCPX (reported in the last row of Table 3). Depending on the control variables included in the model, the markdown revenue increase due to OCPX ranges between 12.3% to 14.8%.

5. Conclusion

Our work contributes to the practice of revenue management in omnichannel retail with innovations in demand forecasting and large-scale network price optimization that are essential to manage digital-era supply chains.

We develop a methodology for forecasting omnichannel network demand which can forecast store demand and online demand at a SKU-location level and in particular, quantify channel preferences of consumers, including the censored no-purchase option. Many retail supply chain professionals expressed concerns with their firms’ IT to support effective omnichannel demand planning. As one executive put it, “We end up either leaving money on the table or losing even more money in markdowns because we don’t have the tools to make the right demand planning decisions.” The executives stressed the need to better predict the origin of demand, since it is important for inventory and fulfillment planning. Our methodology fills this need, and can be used beyond price optimization.

We develop a price optimization model that explicitly accounts for cross-channel interaction due to channel substitution (demand) and cross-channel fulfillment (supply). Our model combines ideas from dynamic pricing and capacity control in order to address the unique features of omnichannel. An omnichannel strategy requires integrated technology tools, and the OCPX solution is an industry-first integrated solution that combines customer choice driven channel pricing and cross-channel fulfilment planning within a single system. This scalable solution can be used, more generally, to price resources in shared inventory systems. OCPX has been tested for clearance pricing at a major U.S. retailer, and demonstrated tangible improvements.

Building this revolutionary integrated system required multiple technical breakthroughs, and novel patent-pending methods in order to meet the unique requirements of omnichannel retail. Our teams have successfully worked with three major US retailers thus far to implement omni-channel merchandising solutions, with several more in the pipeline. As a recognition of our efforts, IBM Research awarded our team the Outstanding Technical Achievement Award in 2015 [O3].

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1 From the 2016 State of the Retail Supply Chain interviews of 98 retail supply chain professionals.
Figure 1: Time series data for the channel prices and the channel sales of a Tablet SKU.

Figure 2: The distribution of sales across zones (volume is proportional to the pie size) and its split between the brick-and-mortar and e-commerce channels for 45 SKUs in the Tablets Category.
Figure 3: An illustration of the use case highlighting the differences and hence the benefits of our solution over typical clearance optimization solutions.

Figure 4: Predicted versus imputed/actual market size, e-commerce, and brick sales for a SKU-zone.
Figure 5: Impact of competitors on retailer through revenue-at-risk.

Figure 6: Gain in markdown revenue plotted against store inventory partitions for SFS fulfillment. Each point represents a product category.
Table 1: Average same-channel and cross-channel price elasticities for Tablets Category.

<table>
<thead>
<tr>
<th>Channel Sales</th>
<th>Elasticity to brick-and-mortar price</th>
<th>Elasticity to e-commerce price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brick-and-mortar sales</td>
<td>−1.3</td>
<td>0.7</td>
</tr>
<tr>
<td>E-commerce sales</td>
<td>2.8</td>
<td>−3.9</td>
</tr>
</tbody>
</table>

Table 2: Projected impact of OCPX in business value assessment.

<table>
<thead>
<tr>
<th>Category</th>
<th>Store price †</th>
<th>Online price †</th>
<th>% Change in Sales</th>
<th>Change in Clearance Revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Actual OCPX</td>
<td>Actual OCPX</td>
<td>Online</td>
<td>Store</td>
</tr>
<tr>
<td>Notebooks</td>
<td>81% 93%</td>
<td>90% 85%</td>
<td>+16% −1%</td>
<td>+10% (+$9.0 million)</td>
</tr>
<tr>
<td>Tablets</td>
<td>81% 90%</td>
<td>79% 77%</td>
<td>+15% +10% +11%</td>
<td>+12% (+$2.3 million)</td>
</tr>
<tr>
<td>Accessories</td>
<td>81% 93%</td>
<td>90% 85%</td>
<td>+11% +5% +6%</td>
<td>+6% (+$1.2 million)</td>
</tr>
</tbody>
</table>

†Clearance prices are normalized by regular price

Table 3: Revenue Impact of OCPX based on causal model estimated from pilot data.

<table>
<thead>
<tr>
<th>ln(Avg-Weekly-MD-Rev)</th>
<th>Coefficient</th>
<th>w/o markdown depth</th>
<th>with markdown depth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>$\alpha_0$</td>
<td>1.820***</td>
<td>1.486***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.178)</td>
<td>(0.230)</td>
</tr>
<tr>
<td>ln(Avg-Weekly-Reg-Rev)</td>
<td>$\alpha_1$</td>
<td>0.597***</td>
<td>0.596***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.021)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Avg-Weekly-MD-Inventory</td>
<td>$\alpha_2$</td>
<td>0.004***</td>
<td>0.004***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Treatment * Reg-Online-Share</td>
<td>$\alpha_3$</td>
<td>1.481**</td>
<td>1.483***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.469)</td>
<td>(0.436)</td>
</tr>
<tr>
<td>Control * Reg-Online-Share</td>
<td>$\alpha_4$</td>
<td>0.565**</td>
<td>0.394†</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.263)</td>
<td>(0.248)</td>
</tr>
<tr>
<td>Avg-Online-MD-Depth</td>
<td>$\alpha_5$</td>
<td>-0.865***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.220)</td>
<td></td>
</tr>
<tr>
<td>Avg-Store-MD-Depth</td>
<td>$\alpha_6$</td>
<td>2.070***</td>
<td>2.070***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.318)</td>
<td></td>
</tr>
</tbody>
</table>

# obs 275 275
# treatment 57 57
R-sq 0.832 0.855

Improvement due to OCPX 12.3% 14.8%

* * p < .001, ** p < .05, * p < .1, †p = .11. SKUs with very small durations and rate of sales were eliminated.
Support Letter:
S1. Support letter.

Journal Papers and Supplemental Material:

Other Related Supporting Documents:
http://risnews.edgl.com/retail-news/Office-Depot-s-Pricing-Model--To-Match-or-Not-To-Match92860
This was the independent press release associated with the public announcement of omni-channel pricing solution for basic items made in IBM Global Commerce Summit 2014.
The capabilities of the proposed solution were announced in this conference.
O3. IBM Research Outstanding Technical Achievement Award. 2015.
Omni-channel pricing received the IBM Research internal award under the category of accelerated market introduction achieving a significant level of realized revenue to IBM attributable to Research Asset(s). The nomination also highlighted the newer innovations related to OCPX and its impact on extending the relationship with the client.

Patents:
http://www.freshpatents.com/-dt20151105ptan20150317653.php
http://www.freshpatents.com/-dt20151119ptan20150332298.php
http://www.freshpatents.com/-dt20160155137ptan20160155137.php
http://www.freshpatents.com/-dt20160283882ptan20160283882.php