How to Survive Dynamic Pricing Competition in E-commerce

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ABSTRACT

Pricing on e-commerce platforms is highly challenging. Sellers typically i) rival against dozens of competitors, ii) decide on prices for thousands of products, and iii) face steadily changing market situations. With respect to pricing, the challenge is to circumvent the curse of dimensionality to dynamically price products for a given market situation in a timely manner. In this project, we create a stochastic pricing model by analyzing recorded market data. This pricing model can be applied ad-hoc in less than a millisecond per item, allowing us to react immediately to new market situations. Our pricing approach is currently being applied in practice by a large German book seller on Amazon and outperforms the previous rule-based strategy by over 20% with respect to cash-in per book.

CCS Concepts

•**Applied computing** → **Online shopping;** *E-commerce infrastructure; Decision analysis;*

Keywords

Dynamic Pricing; Oligopoly Competition; Online Markets; Demand Estimation

1. CHALLENGE

Modern market platforms such as Amazon Marketplace or eBay are highly dynamic as sellers can observe the current market situation at any time and adjust their prices instantly. For sellers that handle large inventories, this dynamic is hard to manage as an optimal pricing decision requires handling a multitude of dimensions for each competitor (e.g., price, quality, shipping time, shipping costs, rating). Moreover, financial aspects such as discounting as well as inventory holding costs have to be taken into account.

In this project, we partner with *adanbo GmbH*. adanbo is among the top 10 sellers for used books on Amazon in Germany with an inventory of over 80,000 distinct books (ISBN), each with multiple items (1-20). Our seller can decide – to some extent – on the replenishment of used books (by choosing purchase prices). However, supply is limited and it is not possible to directly reorder specific books. Hence, the challenge is to extract as much profit as possible from a given number of books (inventory level) in a reasonable amount of time.

The pricing strategy of our project partner is characterized by a rule-based system that has been developed over the past years by carefully adjusting rules to lessons learned from selling books on Amazon. As our project partner has more than 10 years of experience in the market, we consider his strategy to be effective and accurate. However, market dynamics are increasingly sophisticated making rule-based strategies increasingly hard to handle and maintain.

Our goal is to develop a pricing strategy that maximizes expected discounted long-term profits while taking into account the constraints mentioned above. We seek to compute data-driven pricing strategies that are applicable even for large inventories.

2. DATA-DRIVEN PRICING MODEL

The project is devoted to revenue management [3] and combines theory of dynamic pricing research and its practical application [1, 2]. To be able to set up a dynamic model in order to compute optimized prices, we need to estimate sales probabilities. We use logistic regression analyses to quantify how offer prices and specific market situations affect sales. We consider up to 10 offer dimensions (e.g., price, quality, ratings, feedback count, shipping time) per competitor for a particular market situation.

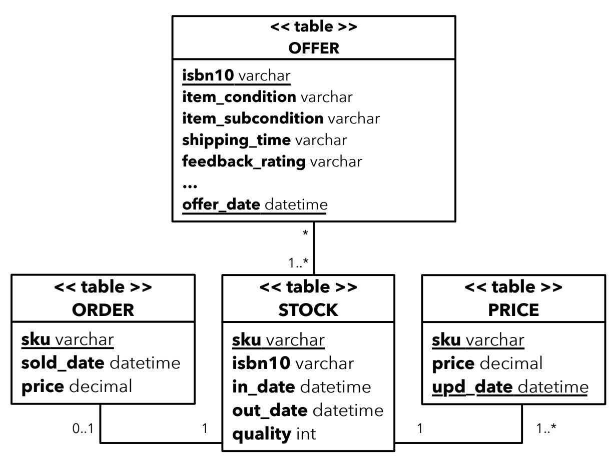

Figure 1: Overview of normalized data set.

The data set that we use for the regression analysis con-

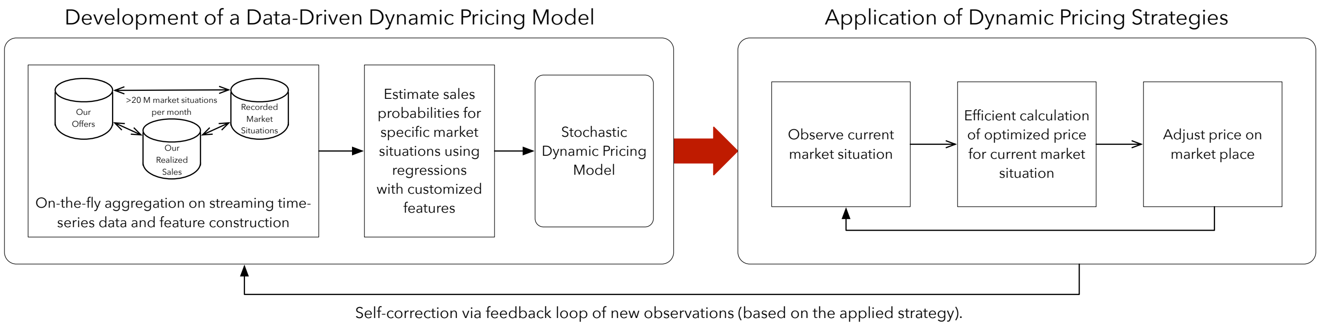

Figure 2: Two-phase process of the data-driven pricing strategy.

tains both the requested market situations from Amazon as well as adanbo's own data (offers, sales, and inventory; see diagram in Fig. 1). Adanbo requests market situations for each offered book every two hours (i.e., >20 M market situations per month which result in >140 M single competitor observations per month). We join this data on the fly with adanbo's price updates, placed orders, and stock data to create the required observations and the corresponding features. Working directly on the raw time-series data provides us with more flexibility, e.g., when regressing only a subset of comparable market situations. We use 30 customized features, e.g., the price rank of our offer price within the competitors' prices. The dependent variable is the number of realized sales of a certain book in a certain time interval. As a result, we are able to predict sales probabilities for any offer price and for any market situation.

Based on estimated (conditional) sales probabilities, we set up and calibrated a suitable dynamic model. Using efficient solution techniques, we are able to compute optimized prices for current market situations. The application of our dynamic pricing strategy works as follows: First, we observe current market situations for our products, we then calculate optimized prices according to the model, and finally adjust prices on the market platform (see right-hand side of Fig. 2). This procedure is repeated every two hours or in case of changing market situations. This way our strategy is able to respond immediately to new situations as prices can be adjusted in milliseconds. Moreover, the new incoming sales observations are used to further improve the strategy by estimating demand more accurately, see Fig. 2.

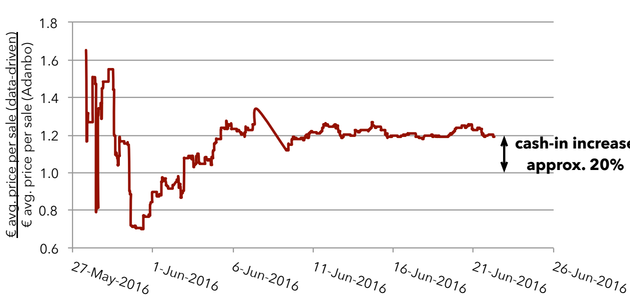

Figure 3: Comparison of average price per sale over time: data-driven vs. adanbo's strategy.

Table 1: Comparison of adanbo's and our data-driven strategy.

	Group size	Sold	Avg. price per sale
adanbo's strategy	3,535	22%	4.34 EUR
data-driven strategy	5,502	17%	5.30 EUR

3. RESULTS

Our data-driven approach is currently applied by our project partner adanbo. We compare our strategy with adanbo's established rule-based strategy for two similar test groups of books (see Table 1). The data-driven strategy sells less aggressive and more profitable. Fig. 3 shows the ratio of the average prices per sale over time. Around two weeks after the begin of the comparison, the advantage of the data-driven strategy averages around a cash-in increase per book by approximately 20 percent.

Note, the model's discount factor allows to control the strategy's aggressiveness and in turn the speed of sales. As a next step, we'd like to evaluate different levels of aggressiveness and their impact on profitability.

4. CONCLUSION

We presented a data-driven pricing approach for competitive sales applications. With our strategy applied, profits can be significantly increased. Moreover, by using the model's discount factor as a management instrument the seller is able to smoothly balance profits, revenues, and the speed of sales.

5. REFERENCES

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