Capturing Consumer Value through Predictive Analytics in Dynamic Consumer Pricing

Jack S. Doig

Northwestern University

Abstract

Organizations are increasingly using dynamic pricing to in order to capture more consumer willingness to pay. In industries such as air travel, hotel rooms, online retail and taxi services, predictive analytics is employed to analyse the market, adjust prices in real time and capture latent consumer value.

Several conditions have given rise to dynamic pricing. Firstly the availability of consumer data and analytical tools allow for better understanding consumer behaviour and targeting. Secondly, pricing can be adjusted and delivered in real-time through mobile devices and e-commerce tools. Finally, given the cost of price comparison for a consumer today is virtually zero, there is increasing necessity to remain price competitive.

At the core of effective dynamic pricing is understanding the consumer demand curve. Predictive models are used to segment clients and generate a localized and dynamic demand model, integrating information such as competitor pricing, consumer behaviour and profiling, as well as time sensitivity. Finally, available supply is used to determine the optimal price.

This paper explores the key inputs and predictive models used in dynamic pricing, the outcomes for management and the limitations of its use. The different models of UBER, a dynamically priced taxi service, Amazon.com, an online retailer, and the Marriott and Intercontinental Hotels chains are examined to explore these key elements.

Key inputs and Methods of dynamic pricing

There are a vast range of inputs to the pricing models, for example Marriott hotels reports 180 variables (Hormby et al. 2010), this paper explores the most common and important inputs across the industries.

Customer segmentation is a key starting point in all the models examined. A different pricing model is then generated by segment. Marriott Hotels segments its client base using classification and regression tress (Hormby et al. 2010). UBER has split its taxi service into five segments, each with their own pricing model. Customer profiling, or first degree price discrimination, has been used by Amazon.com (Harford. 2005) in order to target individual consumers.

In the hotel industry, competitor pricing is a key input into the demand model, and is a critical component for the Intercontinental Hotels model (Koushik, Higbie, and Eister, 2012) in responding to competitor pricing. Similar Amazon can change its prices many times per day in response to competitors. In contrast, in markets where it is the only dynamic pricing operator, UBER adjusts pricing to maximise profits with no consideration of the existing taxi industry.

Consumer Behaviour online is another critical input, for UBER, requests for quotes from mobile devices is the most important variable in predicting current demand. Similarly, Amazon.com uses browsing activity as an input to its pricing algorithm, with heavy browsing indicating positive demand.

Time of year and time-proximity to the service being delivered are other key inputs. A hotel room or taxi will cost more on New Year’s Eve, while lower prices will occur further from the date of product delivery.

This data, having been cleaned, can be used in univariate and regression analysis to determine which input variables are most important, and pricing curves are then fitted to each segment using a logistic curve. This is the method used by Marriott (Hormby et al. 2010).

Finally, supply plays an important role in predicting the optimal price. In the hotel industry, inventory is both constrained and perishable, so the pricing model takes into account both units available and time-to-perish. For UBER, present supply is constrained to the taxis on the street, however higher prices increase supply of freelance taxi drivers, which is in turn is fed back into the pricing model in real-time.

Contribution to management and Limitations of dynamic pricing

Operating a dynamic pricing model can optimize company revenue as it delivers time, inventory, consumer and competitor sensitive pricing and captures more consumer surplus. The Intercontinental Hotel group reports an uplift in annual profits of $145 million or 2.7% increase in revenue per room (Koushik, Higbie, and Eister, 2012) following the introduction of a predictive pricing model. It can also make industries more efficient, UBER has created industry value, thereby attracting increased taxi supply to meet unmet demand, and creating a better service to end clients who would not have otherwise had a taxi (Surowiecki 2014).

Furthermore, analytics removes bias and intuition from the pricing process. 30% changes in the Residence Inn prices in Baltimore were met with scepticism by the experienced hotel managers, however they experienced no lost occupancy at higher rates (Esposito 2011).

In contrast, integrating competitor pricing into a predictive model can encourage a price war and destroy industry profits. A further limitation is that dynamic pricing is successful only where arbitrage can be limited, as airline tickets, hotel rooms, and taxi rides are not easily resold over time. Dynamic pricing can further incur a goodwill cost on the organisation; Regular customers can be alienated as price fluctuates over time, and the company can be accused of price gouging at times of extreme demand.

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