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Retail Therapy

Driving Profits with Predictive Data Analytics and Personalisation

MONASH University
Business and Economics

The Language of Data

Big Data, Business Intelligence and Predictive Data Analytics

This glossary may help navigate the terminology of data analytics.

Predictive data analytics is the practice of formalising insight from a body of data, usually by means of *statistical modelling or machine learning* (see below), and then projecting that insight into the future to aid decision-making. High-profile examples of predictive data analytics include US Target predicting customer pregnancies and delivery dates from shopping data[1], and the prediction of hidden personal traits like political affiliation, religion, and sexual orientation from Facebook Likes[2].

Statistical modelling involves building mathematical replicas of real world phenomena to predict future outcomes, along with estimates of how reliable these predictions are. There is a body of experimental evidence showing that statistical prediction consistently outperforms expert predictions. Recent research indicates that combining human judgement and statistical models together yields even better results[3].

Machine learning refers to using complex algorithms and computation to identify patterns evident in data and make future inferences about them. For example, Australia Post uses machine learning to read and understand hand-written postcodes on envelopes. Machine learning is sometimes referred to as *data mining*.

Data scientist is a title for people who perform predictive data analytics. While the specific applications depend a lot on the industry they work in, data scientists are fluent in the statistical and programming skills required to analyse data and build models to make predictions.

Big Data is an industry of hardware, software, and consulting centred on the collection, storage and use of data of a substantial size (i.e. trillions of bytes – around the total size of Wikipedia's text and images). Big Data can be characterised by three Vs: Volume, Velocity and Variety[4], referring to large amounts of data, transacted at high speed and originating from a variety of sources or representing a variety of things. While Big Data applications often include *predictive data analytics*, the latter applies to data of all sizes. In addition, practical applications of *predictive data analytics* are available to the vast majority of companies without the large investments and extensive IT demands typical of Big Data deployments. A 2012 Microsoft study found that half the analyses being run on servers at Yahoo and Microsoft were small enough to fit on a desktop computer, and 90% of analyses at Facebook would fit on a single server costing around $5,000.

Business Intelligence (BI) is a retrospective (as opposed to predictive) form of data analytics, typically dealing with averages and totals. Business Intelligence tools report current and historical data, usually as customisable charts or tables. However, a typical BI user interested in making forward-looking decisions would have to resort to eyeballing a series of reports to come up with their own predictions. This is a time-consuming and relatively error-prone process that is generally less accurate than using *statistical models or machine learning*.

Driving Profits with Predictive Data Analytics and Personalisation

Summary

- Modern personalisation methods require customer-centric data, individualised treatments and predictive data analytics.
- Personalisation drives profit through key components of retailing, including traffic, conversion, revenue per sale, and margin.
- Benefits from personalisation can be obtained incrementally through predictive data analytics without undertaking long projects or large investments.

Personalisation: The Key to Sustainable Customer Relationships

Tough economic conditions and increasingly savvy consumers have made the retail environment fiercely competitive. Customers are more sophisticated than ever comparing prices in-store on mobile devices; publicising the clever promotions but also negative customer service experiences on social media; and importing items from overseas if their demands for product variety, timeliness, or price are not satisfied locally. The advance of technology is a double-edged sword that threatens traditional retail methods, but also provides new opportunities to reach and engage customers. Customer personalisation is one facet of retail that has been transformed by technology.

In the past, the store manager would greet familiar customers. Knowing their preferences, the store manager could guide customers to appropriate products, highlighting features they would be most interested in – described as *personalised* service. Today, technology enables the same process to be deployed consistently across all sales and communication channels – physical store, online, mobile, e-mail, social media – irrespective of geography, at lower cost, and for all customers (not just those whom sales staff recognise). Fundamentally, personalisation is about tailoring interactions to the customer, using insights gained from all available information about the customer.

Modern customer personalisation is the natural successor to segment targeting, whereby customers would be clustered into half a dozen archetypes (e.g., "Discount Dorothy") and treated accordingly. Today, however, technology allows retailers to target individual customers' *actual* preferences automatically. Two developments have made this possible: the collection of detailed customer data on personal characteristics and behaviour, and predictive data analytics that allows decisions to be based on scientific expectations of future customer behaviour. In this ACRS Retail Therapy whitepaper, the relationship between predictive data analytics and modern retail customer personalisation methods is introduced. Some of the key issues involved in implementing a customer personalisation program are also discussed.

Personalisation Drives Profit

Personalisation is an especially powerful method of moving the needle on the key drivers of retail economics because it is applicable at every step of the purchase process.

Profit = Traffic x Conversion x Revenue per Sale x Margin

Increased traffic: Personalisation makes a customer feel catered to and understood, and deepens engagement with the brand, which increases the likelihood of further purchases. By providing the right products at the right time, a brand becomes more relevant in customers' lives. Promotions for public holidays and seasonal celebrations are widely practised; understanding and anticipating personal buying rhythms – such as friends' and relatives' birthdays, or participation in seasonal activities – can give a brand an real edge.

The expression of preferences (e.g. in Amazon wishlists or Pandora music ratings) can be an enjoyable activity for customers, while investing them in a platform and promoting a brand to their friends.

Increased conversion: Personalised recommendations promote products most interesting to a customer, which increases the likelihood that he or she will make a purchase. In situations where a customer is browsing without specific buying intent, these recommendations aid product discovery and can convert that browsing activity into a sale.

Pricing is a very direct way to affect conversion rates, but experience has shown that customers can rail against personalised prices[6]. However, offering *similar* but not *identical* products to different people at different prices – prevalent in the air travel and insurance industries – can lead to the same conversion rate improvements as personalised prices.

Increased revenue per sale: Most retailers already understand that a timely recommendation or offer at point of sale can increase basket sizes (e.g. buy one more item to get a free bag); a personalised approach makes that even more effective, by gauging which suggestion is most effective for the customer and situation.

Another way personalisation drives revenue is by matching more expensive products to customers who prefer luxury goods. For example, one travel site discovered that Mac users preferred upmarket hotels and has experimented with displaying pricier accommodation to Mac users compared to PC users[7].

Increased margin: Targeted discounting to price sensitive customers avoids indiscriminate fire sales that give away value. Predictive data analytics can identify when customers are not price sensitive and suggest appropriate add-on products that are likely to be higher margin. A more detailed, data-driven understanding of the customer and context allows you to differentiate between transactions that are price-sensitive and those where other factors, such as service, convenience and luxury, are more important. For example, Sunglass Hut tries to upsell a AU$15 "care kit" on every sale, which increases the margin on a typical sale substantially but does not appeal to everyone, for example repeat customers who already have a kit. A personalised approach might include offering laser-etched monogramming at AU$100 to luxury-oriented consumers, instead of the smaller ticket, single-sale "care kit".

Personalisation Benefit Model

Benefit = Individual Customers x Personalised Treatment

Personalisation achieves its results by combining customers and treatments, using predictive data analytics as the "multiplier" that merges these two components.

The customer component involves collecting as much detailed, relevant information about each customer as possible to collate: who they are, what they like, how often they shop, and what they buy. The key is to organise this data at an individual level, and make this structure available when executing personalised treatments.

Personalised treatments are promotional actions your brand performs on customers, based on *who the customer is*. Treatments typically involve communications channel activities (such as advertising, offers, recommendations and catalogues), or sales channel services (like checkout, wrapping, shipping and store credit). The more specific the treatment is to the customer, the more personalised the treatment. For example, personally-engraved products for premium loyalty members and personally-addressed sales letters are highly personalised treatments.

A key consequence of the Personalisation Benefit Model, one component without the other does not generate results. A keen understanding of each customer without personalised treatments remains a generic and undifferentiated brand experience; and highly customisable experiences without customer insight miss the mark. Predictive data analytics is the tool that connects individual customer insight with personalised treatments in a way that scales across an entire business.

Customer-centric Data is the Raw Resource

The first fundamental ingredient of the Personalisation Benefit Model is to know customers at an individual level. To do this, data about customers must be organised individually. It is insufficient to know that 60% of men prefer electric shavers to manual razors – the data needs to be interrogated to discover *which* male customers prefer electric shavers and which prefer razors. In essence, the customer needs to be at the centre of a retailer's data universe.

Today, many brands run a loyalty program; many transactions are performed by credit card. This essentially means that the customer is identified at the point of sale. Many firms also record all customer communications in a Customer Relationships Management system (CRM). Many retailers have an online and mobile storefront in which the activities of customers can be meticulously tracked. Instead of a handful of facts about a small list of frequent customers kept in the head of one store manager, a vast repository of information – every preference, every product enquiry, every purchase and multiple contact channels, about each and every customer, across every store and every channel – can be the foundation of a smooth, consistent and personalised brand experience.

Personalised Sales and Communication Channels are the Levers

The second fundamental ingredient of the Personalisation Benefit Model is the application of tailored treatments to customers. Because customers experience a brand through various channels, these channels need to be capable of personalised treatments.

In non-personalised (or *impersonal*) channels, all customers receive uniform treatment – the same advertising, the same discounts, the same service, based on a fictional "average" customer. At best, customers are sorted into broad segments (e.g. men vs. women, young vs. old). Impersonal channels constrain the potential to exploit a deeper understanding of customers and to go beyond generalised and stereotyped treatments.

In a personalised channel, the decision on how to treat a customer for each interaction can be shaped by all of the knowledge about that customer, leading to individual, personalised treatments. There are countless approaches and strategies for personalising sales and communications channels. Generally, they require data about the customer being fed directly to the point of interaction. Some examples of how treatments within channels can range from impersonal to personal are described below. Amazon's marketing e-mails compete with each other so that only the most valuable one (for each particular customer) is sent. As a result the customer's inbox is not flooded, and the customer is less likely to ignore or opt-out of communications from Amazon.

E-mail: We all have the experience of dealing with large volumes of impersonal and repetitive "spam" e-mail. While the direct monetary cost of sending an irrelevant e-mail is negligible, the cost to the credibility of an e-mail channel is not[8].

Mailbox catalogues: At one end of the spectrum, catalogues that are designed and printed once and delivered everywhere (often, to customers and non-customers alike) are very impersonal. At the other end of the spectrum, catalogues customised to include specific products or coupons, printed bespoke for each customer using a print-on-demand methodology, are a highly personalised treatment. An example is the US Target's inclusion of maternity goods in catalogues for expectant mothers[9].

Mobile apps & SMS: SMS advertising can be more effective than e-mail – with 98% open rates, more engaged recipients, and more location-awareness[10]. Impersonal and "spammy" messages that treat the recipient as a member of a broadcast list squanders the potential of SMS. On the other hand, timely, location-sensitive promotions that factor in loyalty account information can provide significant value – making it possible to deliver a personalised offer when the customer is physically located near a store, enticing them to visit. A unique characteristic of the mobile channel is the ability to deeply engage customers during commutes and in leisure time away from a desk. Further, innovative approaches have the potential to capture this undirected time for the benefit of a brand. For example, collecting personal preference information via a fun mobile app that asks the user to rate successive photos of fashion items.

Web store: Because of its digital nature, the web offers a tremendous opportunity for personalisation; however many retailers are still just catching up and offering the stock standard "product catalogue with shopping cart" web store. In the last decade, Amazon has led the way with a personalised online shopping experience, where every webpage served is composed only for the customer viewing it, with highly specific recommendations and offers based on the customer's browsing and purchase history.

Physical store: Few physical stores offer a personalised experience. Even after a loyalty card is presented at the point-of-sale, opportunities for small but memorable personalisation touches such as greeting the customer by name are often missed. At the advanced end of the spectrum, some retailers have experimented with complementing the physical store shopping experience using mobile apps with location sensing, sending personalised offers when a customer enters a store, or alerting shop staff to the presence of VIP customers. For example, Coles distributes custom coupons online that are redeemed in-store as part of their loyalty program.

Personalised channels are how customers experience a brand's personalisation efforts. If channels are impersonal and generic for every customer, the brand experience will not appear personalised to customers no matter how much data is collected about them.

Predictive Data Analytics is the "Multiplier"

Predictive data analytics is the technical capability that allows brands to accurately connect customer data with a tailored brand experience, ultimately helping a brand to determine the most effective treatment for each customer given their personal characteristics, past history of interactions, and other like customers. For each application of predictive data analytics, the business benefits sought should shape the nature of the analysis – usually these are tactical benefits supporting a greater strategic objective. If a brand is trying to increase conversion through discount offers, the focus will be on modelling customer responses at various levels of discounting. If a brand is trying to encourage higher traffic through VIP shopping events, the emphasis will be on determining which customers react most favourably to special events and priority access. Recommending items similar to those purchased in the past may work for some products (for example consumer packaged goods), but be inappropriate for others (for example recommending discount televisions after the purchase of a premium home theatre system). Domain knowledge is vital to framing the objectives of the optimisation.

The fact that predictive data analytics is focused on delivering discrete tactical business benefits makes its application very scalable. As such, retailers can choose to incorporate predictive data analytics bit-by-bit, selecting a pace of adoption that suits their aggressiveness and risk appetite. For example, piloting personalisation techniques on a handful of stores in Melbourne; later expanding to include Sydney once the benefits are proven; and finally, a countrywide or even worldwide rollout.

Ilustrative Example

Suppose a brand is looking to enhance profitability on the web store through personalised recommendations. The idea is to build a statistical model to predict, for each customer, what recommendation creates the most value when you make it, compared to when you do not (i.e. what recommendation has the *highest marginal value*). This is analysed by comparing two scenarios: a *treatment* scenario where a recommendation is made and a base scenario where no recommendation is made at all. The expectations in the scenarios are predicted by the statistical model and based on a variety of data. This information includes what the customer has shown interest in or purchased, what similar customers have purchased, the response to previous recommendations and other such relevant factors.

The data for creating the statistical model is best collected by running a series of *controlled experiments*. These are experiments where some customers are made recommendations and others not. In general, the more customers included in the experiment, the more the results can be generalised and the more detailed the insights gained. Controlled experiments are the gold standard technique to differentiate between results that occur *because* of the actions (i.e. the treatment) and results that are simply business as usual.

Figure 1 Customer profile of Margaret Taylor

Margaret Taylor
42 years old, female, lives in Richmond, Victoria
E-mail address: maggietails@hotmail.com
InClub member #29002
Total spend to-date: $2,134.45
Total spend, last 12 months: $1,098.30

Last 20 transactions
10:05am Sun 2 Feb 2014: RETURN SKU LEV/13123 Levi's 501 Jeans, Medium Stonewash, 31W 34L, -$99.95, Melbourne City Store; served by Kelley Johnson
10:19am Sat 1 Feb 2014: PURCHASE SKU LEV/13123 Levi's 501 Jeans, Medium Stonewash, 31W 34L, $99.95, Melbourne City Store; served by Linda Hayes
2:22pm Fri 3 Jan 2013: PURCHASE SKU BAS/8829990 Basque Rolled Cuff Sleeveless Shirt, White, $69.95, Chadstone Store; served by Jill Mayer
...
Web activity, last 30 days
7:12pm Mon 3 Mar 2014: Mac OS X 10.9, Safari 7.0.2; Browsed 2 products: SKU MAP/9922 Marco Polo Long Sleeve Floral Longline Shirt, SKU BAS/8829001 Basque Soft V Neck Shirt
8:12pm Thu 27 Feb 2014: Mac OS X 10.9, Safari 7.0.2; Browsed 1 product: SKU PIP/30311001 Piper Check Shirt; Added 1 item to Shopping Cart: SKU PIP/30311001 Piper Check Shirt; CART ABANDONED
...
Mobile activity, last 30 days
12:31pm Wed 26 Feb 2014: iPhone 5, iOS 7.0.1; Checked-in at Melbourne City Store
...
E-mail offers sent, last 30 days
5.30pm Thu 27 Feb 2014: To maggietails@hotmail.com; 10% off selected lines
...
and many more facts

A. SKU	B. Price	C. Margin	D. Likelihood of purchase, base	E. Likelihood of purchase, treatment	F. Difference in expected margin
BAS/0000001	$79.95	$51.95	0.00105%	9.01%	**$4.68**
BAS/0000002	$79.95	$44.95	0.00110%	9.12%	**$4.10**
(...all available SKUs)					

Figure 2 Profitability characteristics of Margaret Taylor

Figure 1 depicts a customer profile extracted from a hypothetical CRM database for one customer, Margaret Taylor. The transaction entries shown are typical data points that provide the inputs to a recommendation analysis. Figure 2 is a table of Margaret Taylor's profitability characteristics for every available product SKU. Columns D, E and F of the table are computed by the statistical model, using a selection of data from the profile and each SKU in turn (for example sales history, other SKUs frequently purchased together, etc.). We can now rank candidate product recommendations by column F: the increase in benefit between recommending and not recommending each product. Products at the top of the list are the optimal recommendations for maximising profit.

There are two mistakes that are easily made when thinking about recommendations. One is ranking by D, the likelihood that a customer will buy this item without you recommending it. The other is ranking by E, the likelihood that a customer will buy this item when it is recommended. Neither of these prioritisations correspond to the true economic value of the recommendations. Understanding which items a customer is likely to buy (D) is interesting. However, by definition, these are items that the customer *would buy anyway*. The likelihood that the customer will purchase the item if it is recommended (E) is also interesting. However, it ignores the fact that a customer may already have a very high likelihood of buying it regardless – so the recommendation does not add much additional benefit. The difference in the amount of profit that you make *because of the recommendation* (F) is the most meaningful metric that the recommendation should seek to achieve – and the one that is in line with the overall business objectives.

The analysis described above would be performed for each customer visiting a web store, creating an opportunity for to enhance an online storefront experience by highlighting products with the highest expected value for a firm, perhaps in a "Recommended for You" section. An omni-channel retailer may further consider how to consistently extend these product recommendations across all of their touch points.

As new customers visit your web store and existing customers generate more activity, the products recommended to them will evolve appropriately. However as old products are retired, new products become available, and seasonal trends take effect, it is important to refresh the recommendation engine to ensure that it is up-to-date.

This case study depicts an elementary component of a personalised retail experience. More detailed and sophisticated personalisation methods exist. For example, mixing in less-than-ideal recommendations in a set of recommendations to create an anchoring effect that can improve the effect of the optimal personalised recommendation[11] . Indeed, US Target started hiding their optimal personalised offers in amongst other offers to avoid "spooking" customers[12]. Another advanced technique is analysing the words and phrases used in communications to maximise the response rate. By experimenting with several different versions of a communication on a pilot group and analysing the effect on different people, the most effective version for each individual can be sent out – a technique that many political commentators attribute the success of the Obama fundraising campaign to[13].

Other Questions That Can Be Answered By Predictive Data Analytics

Personalisation is just one of many business optimisation techniques made possible by predictive data analytics. Other examples include:

How do I incorporate social network information to understand opinion leaders?

Social networks can be rich sources of customer insight, but the data is nebulous and difficult to interpret. By merging sales data with data about the volume and content of social media messages, the shape of the network and information flows, it is possible to discover the most important influencers in your customer network and in turn, determine how to influence them.

What components of customer engagement are important to my bottom-line?

While actual purchases are the ultimate sign of engagement, predictive data analytics can estimate how much auxiliary activities such as reading newsletters, clicking advertisements, or searching for products correlates to later purchase, and thus, how much investment in these activities will drive profits.

How can I capitalise on patterns in product purchases?

While it is possible to manually identify related products often purchased together, predictive data analytics can extend this analysis across your entire product range and also make projections about future product ranges. Insights can then be fed into wide-ranging decisions including buying, logistics, merchandising, product bundling, pricing, offers and recommendations. For example, creating a product bundle to make it easier for customers to buy a popular combination of products.

How do seasonality and product lifecycles affect sales?

Given the right data, predictive data analytics can correlate sales with seasonal events such as weather, public holidays and sporting events, as well as predictable trends such as product lifecycles, to estimate how much these circumstances affect your business. More accurate demand forecasting can reduce stock-outs and improve warehouse efficiency.

Conclusion

Modern personalisation techniques connect customer-centric data with individualised treatments to maximise the value of a retailer's relationship with existing and potential customers. These methods have been enabled by the advance of information technology and predictive data analytics, which make well-informed, accurate and effective personalisation scalable across every store and channel.

Personalisation using predictive data analytics does not necessitate long projects or large investments, evolving gracefully from limited pilot projects to full-scale omni-channel experiences. For most organisations, running pilot or scoping programmes can demonstrate the scale of the value available, before investing in more intensive applications of predictive data analytics.

Finally, personalisation is just one of many retail problems that predictive data analytics can help solve – the range of applications is diverse and can address elements on both the revenue and cost sides. It has been well over a decade since predictive data analytics started unlocking new opportunities for leading global retailers. With the increasing sophistication of consumers and the competition, there is no better time for Australian retailers to build this capability.

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