Predictive Marketing: Anticipating Market Demand with Proactive Action

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Abstract

Traditionally, marketers rely on descriptive statistics that explain past behavior and use their intuition to make smart guesses on what will happen next. In predictive analytics, most of the analysis is carried out by artificial intelligence (AI). Past data are loaded into a machine learning engine to reveal specific patterns, which is called a predictive model. By entering new data into the model, marketers can predict future outcomes, such as who is likely to buy, which product will sell, or what campaign will work. Since predictive marketing relies heavily on data, companies usually build the capability upon the data ecosystem they have previously established. With foresight, companies can be more proactive with forward- looking investments. For instance, companies can predict whether new clients with currently small transaction amounts will turn out to be major accounts. That way, the decision to invest resources to grow the specific clients can be optimal. Before allocating too many resources into new product development, companies can also use predictive analytics to help with the filtering of ideas. All in all, predictive analytics leads to a better return on marketing investment. Predictive modeling is not a new subject.

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For many years, data-driven marketers build regression models to find causality between actions and results. But with machine learning, computers do not need a predetermined algorithm from data scientists to start uncovering patterns and models on their own. The resulting predictive models coming out of a machine learning "black box" are often beyond human comprehension and reasoning. And this is a good thing. Marketers are now no longer restricted to past biases, assumptions, and limited views of the world when predicting the future.

Predictive analytics uses and analyzes past historical data. But it is beyond descriptive statistics, which is useful for retrospectively reporting past company results and explaining the reasons behind them. Companies with a vision of the future want to know more than just what happened in the past. It is also beyond real-time analytics that is used for providing a quick response in contextual marketing or testing marketing activities.

Predictive analytics examines past behaviors of customers to assess the likelihood that they will exhibit similar or related actions in the future. It discovers subtle patterns in the big data and recommends the best course of action. Very future-oriented, it helps marketers to stay ahead of the curve, prepare marketing responses ahead of time, and influence the outcome. Predictive analytics is critical for proactive and preventive measures, which is perfect for marketing planning purposes. With predictive analytics, marketers have a powerful tool at their disposal to enhance decision making. Marketers can now determine which market scenario is likely to happen and which customers are worthwhile to pursue. They can also assess which marketing actions and strategies have the highest likelihood of success before launching them—significantly reducing the risks of failure.

Predictive Customer Management

Targeting and serving a customer without knowing the future income the customer will bring is a marketing investment nightmare. Marketers need to decide whether to spend customer acquisition and service costs—for advertising, direct marketing, customer support, and account management—to get and nurture the customer. Predictive analytics can help marketers make this decision better by estimating the value of a customer. The predictive model used for customer management purposes is called the customer equity model. It measures customer lifetime value (CLV), which is the present value of projected net income generated from a customer during the entire relationship with the company. It provides a long-term, forward-looking view on the return of investment, which is critical because most customers might not be profitable in the first or second year due to the high customer acquisition costs. The concept is most relevant for business-to-business (B2B) companies and services companies with long-term customer relationships, such as banks and telcos. Companies serving corporate clients have massive customer acquisition spending, especially for trade shows and salesforce costs. Similarly, banks spend a lot of money on advertising and sign-up bonuses while telcos are well- known for their mobile device subsidies to acquire customers. For companies in these sectors, the marketing costs are too high for one-time transactions and short-term relationships. The role of analytics in estimating the CLV is to predict a customer's response to the upselling and cross-selling offerings. The algorithms are usually based on the historical data of which products were purchased as a bundle by customers with similar profiles.

Moreover, marketers can predict the length of relationship with each customer. Predictive analytics can detect customer churn and, more importantly, discover reasons for churn. Thus, companies can develop effective retention strategies to prevent customer attrition. For those reasons, predictive analytics not only forecasts but also improves CLV. Once the customers are profiled and their CLVs are calculated, marketers can implement next-best-action (NBA) marketing. It is a customer-centric approach in which marketers have orchestrated a clear, step-by-step action plan for each customer. In other words, it is a marketing plan for the "segments of one."

With multichannel interactions from digital marketing to the salesforce, marketers guide each customer from pre-sales to sales to post-sales service. In each step, predictive analytics can help marketers determine which move they should make next: send more marketing collateral, do a product demo, or send a team to make a sales call. In a simpler form, businesses can also perform CLV-based customer tiering, which is essentially a resource allocation tool. The leveling dictates how much money companies should allocate to acquiring and retaining a customer in a particular tier. Marketers can prioritize which customers to build a relationship with and drive them to higher levels over time. It also becomes the basis for the different customer interfaces that companies provide to different customers. That is, customers with higher profit contribution will get access to a dedicated customer support team while others will get access to an automated digital interface.

Predictive Product Management

Marketers can utilize predictive analytics across the product lifecycle. The predictions can start early in the product development ideation. Based on an analysis of what attributes work in already-marketed products, businesses can develop new products with a combination of all the right features. This predictive marketing practice allows the product development team to avoid repeatedly going back to the drawing board. Having a product design and prototype that have a higher chance of success in market tests and actual launch will save marketers a significant part of the development costs. Moreover, external information on what is trending and what will resonate with potential buyers also feeds into the algorithms. It allows marketers to be proactive and leverage trends earlier than their competitors. Consider the Netflix example. The media company started to create original content to strengthen its competitive advantage over emerging competitors and lower its content costs in the longer run. And it used analytics to drive decisions on what original series and movies to make.

Predictive analytics is also essential for selecting which product to offer from an existing portfolio of options. The predictive algorithm used is called recommendation systems, which suggest products to customers based on their history and preferences of similar customers. The propensity model estimates the likelihood of customers with specific profiles to buy when offered certain products. It enables marketers to provide customers with personalized value propositions. The longer the model works and the more customer response data it collects, the better the recommendations will be. The recommendation engine is most commonly applied by retailers like Amazon or Walmart and digital services businesses such as YouTube or Tinder. But the application has made its way to other sectors as well. Any companies with a large customer base and a broad portfolio of products or content will find product recommendation engines valuable. The model will help the companies automate the process of matching the products and markets. Moreover, the predictive recommendation model is most useful when products are bought and used together or in conjunction with one another. The modeling involves what is known as product affinity analysis. For instance, people who have bought shirts would probably be interested in buying matching trousers or shoes. And people who are reading a news article might want to read other articles written by the same reporter or learn more about the topic.

Predictive Brand Management

Predictive analytics can help marketers plan their brand and marketing communications activities, especially in the digital space. The main data analysis requirement includes building complete audience profiles and mapping the key ingredients of successful past campaigns. The analysis will be useful to envision which future campaigns are likely to succeed. Since machine learning is a constant endeavor, brand managers can continue to evaluate their campaigns and optimize where they may fall short.

When designing the advertising creative and developing content marketing, brand managers can utilize machine learning to gauge customer interests in various combinations of copies and visuals. Sentiment analysis in social media and third-party review websites can be used to understand how our customers feel about our brands and campaigns. They can also collect data on which digital campaigns drive the most clicks. Therefore, brand managers can create creatives and content that produce optimal outcomes, such as positive sentiments and high clickthrough rates. Predictive analytics can also be a powerful tool to guide content distribution to the right audience. It works in two ways. Companies may design the branded content and then identify what customer segments will be the most effective to reach as well as when and where to engage them.

Alternatively, companies can profile the customers and then predict which content will resonate with them most in every step in their journeys. Customers might struggle to find the information they need in a large pool of content that brands broadcast. The prediction model can provide a solution by forecasting the right audience–content fit that produces the optimal outcome. Thus, marketers can break content clutter and perform a very targeted distribution to the intended audience. In the digital space, businesses may easily track the customer journey across multiple websites and social media. Therefore, they can predict a customer's next move in their digital engagements. With this information, marketers can, for instance, design a dynamic website in which the content can change according to the audience. As customers browse through the website, the analytics engine predicts the next-best content that will gradually increase the level of interest and get the customer one step closer to purchase action.

Collaborative Filtering for Recommendation Systems

There are many techniques to create predictive marketing models from the simplest to the most sophisticated. Marketers will need the help of statisticians and data scientists to build and develop the models. Thus, they do not need to understand the statistical and mathematical models in depth. However, marketers need to understand the fundamental ideas behind a predictive model so that they can guide the technical teams to select data to use and which patterns to find. Moreover, marketers will also help interpret the model as well as the deployment of the predictions into operations. The most popular technique to build recommendation systems is collaborative filtering. The underlying assumption is that people will like products similar to other products they have bought, or prefer products that are purchased by other people with the same preferences. It involves the collaboration of customers to rate products for the model to work, hence the name collaborative filtering. It also applies to not only products but also content, depending on what marketers aim to recommend to the customers. In a nutshell, the collaborative filtering model works according to the following logical sequence:

1. Collect preferences from a large customer base. To measure how much people prefer a product, marketers can create a community rating system where customers can rate a product either with a simple like/dislike (like in YouTube) or a 5-star scoring (like in Amazon). Alternatively, marketers can use actions that reflect preference, such as reading an article, watching a video, and adding products to the wish list or shopping cart. Netflix, for instance, gauges preferences by movies that people watch over time.

2. Cluster similar customers and products. Customers who have rated similar sets of products and have shown similar behaviors can be classified into the same cluster. The assumption is that they are part of the same psychographic (based on like/dislike) and behavioral (based on actions) segments. Alternatively, marketers can also cluster items that are similarly rated by a particular group of customers.

3. Predict the rating that a customer will likely give a new product. Marketers can now predict ratings that customers will give to products they have not seen and rated based on ratings provided by like-minded customers. This predicted score is essential for marketers to offer the right products that the customers might like and will most likely act on in the future.

Neural Network for Complex Predictions

A neural network, as the name implies, is loosely modeled after how the biological neural network operates inside the human brain. It is one of the most popular machine learning tools that help businesses build sophisticated models for predictions. The neural network model learns from experience by processing a large number and a variety of past examples. Today, neural network models are readily accessible. Google, for instance, has made TensorFlow, its machine learning platform with neural networks, open-source software available to everyone. Unlike a simple regression model, a neural network is considered as a black box because the inner workings are often hard for humans to interpret. In a way, it is similar to how humans sometimes cannot explain the way they make decisions based on the information at hand. However, it is also suitable to build models from unstructured data where the data scientists and business teams are unable to determine the best algorithm to use. In lay terms, the following steps explain how a neural network operates:

1. Load two sets of data: the input and the output. A neural network model consists of an input layer, output layers, and hidden layers in between. Similar to how we build a regression model, the independent variables are loaded into the input layer while the dependent variables go into the output layer. The difference, however, is in the hidden layers, which essentially contain the black-box algorithms.

2. Let the neural networks discover connections between the data. A neural network is capable of connecting the data to derive a function or a predictive model. The way it works is similar to how human brains connect the dots based on our lifelong learning. The neural network will discover all kinds of patterns and relationships between each data set: correlations, associations, dependencies, and causalities. Some of these connections may be previously unknown and hidden.

3. Use the resulting model in the hidden layers to predict output. The functions derived from example data can be used to predict the output from a new given input. And when the actual output is loaded back to the neural network, the machine learns from its inaccuracy and refines the hidden layers over time. Thus, it is called machine learning. Although it does not reveal real- world insights due to its complexity, the neural network model coming from continuous machine learning can be very accurate in its predictions. The choice of predictive models depends on the problem at hand. When the problem is structured and easy to grasp, regression modeling suffices. But when the issue involves unknown factors or algorithms, machine learning methods such as neural networks will work best. Marketers can also use more than one model to find the best fit with the data that they have.

Conclusions

Data-driven marketers can stay ahead of the curve by predicting the outcomes of every marketing action. In customer management, predictive analytics can help companies estimate the value of their potential customers before onboarding and determine how much investment to get and grow them. In product management, marketers can envision the sales results of a pre-launch product prototype and determine which product line to upsell and cross-sell from an extensive portfolio. And finally, predictive modeling can enable brand managers to analyze their customer sentiments and decide how to build their brands in the given context. There are several popular techniques of predictive marketing modeling, which include regression analysis, collaborative filtering, and neural networks. Machine learning or artificial intelligence might be utilized to build predictive models. Thus, most marketers will need the technical help of statisticians and data scientists. But marketers must have a strategic understanding of how the models work and how to draw insights from them.

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