Buyer's Guide to Predictive Analytics for B2B Sales and Marketing



Introduction

Today's B2B marketers can choose from a larger and ever-increasing number of predictive analytics vendors. This abundance makes it more likely that a system exists to meet each marketer's particular needs, but harder to find that system among the many alternatives. The challenge is even greater because many marketers are unfamiliar with the details of predictive technology.

This paper is designed to help marketers make a sound choice. At its core is a list of key factors that differentiate predictive systems including explanations of what they are, why they matter, and when they're used. This is surrounded by a general introduction to the topic and followed by advice on how to run your own selection project. The goal is to provide a complete package of information that will accelerate selection and deployment of your own predictive analytics capability.

Let's get started.

Predictive Analytics Basics

Predictive analytics forecast behaviors based on how similar customers have behaved in the past. (For simplicity, this paper will use "customers" to refer to both customers and prospects.) The key is defining "similar," which requires gathering many kinds of data, selecting the ones that best predict behavior, and determining how to combine them. Thus the process begins by associating individual customers with their data, which may include personal and corporate demographics, interests expressed, offers accepted or rejected, products purchased, locations, devices and channels used, and environmental conditions such as economic trends. The systems then find correlations between a particular behavior, such as making a purchase, and other data available before the behavior took place. These correlations are combined using various statistical techniques to build a model that predicts how customers with a specified set of attributes will behave in the future.

It's important to remember that predictive analytics is never perfect. Data may be missing, incomplete, or inaccurate. Algorithms may not use all available data correctly. Predictions are based on averages that will not be correct in every case. Customer behaviors may change over time. Above all, predictive analytics only show correlations between data and behaviors, not how (or even whether) the data actually causes those behaviors. This means a model may contain undetected errors that suddenly become important when conditions change. Marketers must always maintain a certain level of watchful wariness to monitor performance and adjust their methods as necessary.

Imperfection notwithstanding, marketers increasingly rely on predictive analytics because of its advantages over alternative predictive techniques. Bird entrails are

messy. Crystal balls shatter when dropped. Gut instinct often has little basis in fact, while even deep experience can be misleading as marketing changes rapidly. Deductive logic, no matter how impeccable, doesn't fully apply when human buyers are involved. Applied correctly, predictive analytics overcomes all these obstacles, enabling accurate, reality-based decisions that are more easily adjusted as conditions evolve.

Marketing Applications

Predictive analytics can apply to anything from demographics to stock movements to horse racing. Marketing applications include:

- Prospect discovery: identifying "net new" names of potential customers for your product. This has traditionally involved building models against compiled lists enhanced with demographic data such as title and department or business size and industry. More recently, marketers have been able to access additional information such as interests and intent, generally derived from Web behaviors such as content consumption and social media postings. The general approach has been to start with a list of existing customers, enhance them with external data, build a model with the external data, and then apply that model to select prospects with similar characteristics from a universe the vendor has identified by assessing all firms and, in some cases, individuals on the open and social Web.
- Lead scoring: estimating which current leads are most likely to become customers. This is used to prioritize marketing and sales activities to achieve the best results. In practical terms, this lets salespeople concentrate on the most promising leads while other leads are managed through lower-cost marketing contacts such as email nurture campaigns. The process in this case is to start with a database of past leads and build a model that identifies those who eventually reached a goal such as sales acceptance or making a purchase. Scores can be assigned to individuals or companies, can be based on both behaviors and attributes, and can use external as well as company-owned data. Behavior-based scoring measures "engagement" and changes over time; attribute-based scoring measures "fit" against an ideal customer profile and is usually stable. Some systems assign separate fit and engagement scores.
- Enrichment: appending data to existing customer profiles to provide insights about needs and interests. This data is derived from both structured as well as open and social Web sources. Some data can be read directly from those sources, such as company, title, address and telephone number. Other data may need advanced technology to extract into a usable format, such as technologies used (based on job requirements), expertise (derived from past jobs and experience), important events (taken from press releases, blogs and news articles), and growth rate (based on changes over time).

- Recommendations: predictions such as products a company is most likely to purchase, messages they are most likely to respond to, or channels they prefer to communicate through. The predictions are based on detailed data such as purchases of individual products or responses to different types of offers. They often apply collaborative filtering techniques that depend more on correlations among product purchases than on correlations between individual attributes and results. They may also be based on enrichment information, such as opening a new office or launching a new product, that implies a certain set of needs.
- Lead intelligence: providing guidance to sales and marketing people about how to treat individual leads. The key element here is predicting which leads are close to initiating a buying project, making a purchase decision, or otherwise responding to a contact. Models are built by correlating behaviors such as Web searches or page views and social media comments with important outcomes such as requesting a proposal or making a purchase. The goal is to help internal teams apply their time to the most pressing needs. Lead intelligence can also be informed by the product, offer, and channel recommendations provided by content models.
- Customer success: helping customer success, account, service, and support teams anticipate the needs and actions of existing customers. This relies largely on internal data to predict several types of customer behaviors: how they'll use the system, what kinds of help they'll need, what additional products or modules they might buy, and whether they'll continue the relationship. The core application is churn prediction, although there are of plenty others. The required models are broadly similar in terms of correlating system usage with behaviors by previous customers. Some models may also incorporate external data, such as social comments or Web searches that indicate a customer is dissatisfied and considering switching to a new vendor or, more positively, has expanded needs that offer an opportunity for additional purchases.
- Measurement: predicting the impact of marketing interactions and estimating customer value. This requires data that ties interactions to customers and customers to revenues. Assembling complete views of the interactions and revenues for each customer are both challenging. In addition, it takes sophisticated analytics to accurately estimate the incremental impact of individual interactions on long-term value. But such models are increasingly important as marketers move towards automated approaches, such as programmatic media buying, which rely on accurate predictions of a marketing interaction's impact.

Differentiators

Predictive analytics clearly has a lot to offer. But getting started requires choosing the right system, which in turn requires understanding what to look for. The factors to consider fall into three broad categories: data, modeling, and outputs. Here are some important questions to ask in each area:

Data Types

Data is the foundation of predictive analytics. Some systems work primarily with structured data such as customer attributes and transactions. Others add semi-structured data such as Web logs or unstructured data such as social media and Web site content or call notes in CRM. Systems may process and provide data at the company level, or individual level, or both. Applying standard categories to data is important to help systems analyze results effectively despite variations in inputs.

- does the system process and provide data about individuals, companies/accounts, or both?
- what static data does the system use, such as company size and individual title?
- what behavior data does the system use, such as Web page views, purchase history, and promotion responses?
- what derived data does the system use, such as lead status, average purchases, or engagement rating?
- what unstructured data does the system use, such as text of social media content or call center transcripts?
- how does the system process unstructured data to make it useful, for example by identifying people, products or topics that are mentioned or by flagging unhappy customers?
- does the system track information over time, such as frequency of Web site visits or changes in management?
- does the system apply standard categories to data such as title, department, industry, topic, etc.?

Client Data

Systems that work with existing customers rely primarily on data from the company's own systems, such as purchases, Web site visits, email responses, and call notes from sales and customer service agents. The ability to import and use such data is critical for applications that deal primarily with current customers. It is less important when dealing with prospects and leads.

- how does the system import data from client systems: batch file imports, API connections, database queries, etc.?
- are there existing connectors to import data from the systems used by my company?
- what is involved in building a new connector: who does the work, what is the cost, how long does it take?
- what types of data can be imported from client systems?
- are there any limits on the volume of data or how often the data is imported?

Vendor Data

Systems that provide prospect lists or score newly-acquired leads rely heavily on data provided by the vendor since the client will have little information about the individuals or companies. Vendors differ

in the sources they use, geographic regions they cover, and amount of history they retain. Most use a combination of data they have assembled for themselves from Web, social, and other primary sources and data they acquire from third parties such as "intent" networks. Vendors also differ in whether they actually sell new names to clients or will only enhance records the client already has acquired.

- what types of data does the vendor provide and where does it come from?
- how often is vendor-provided data updated and how long are old values retained before being discarded?
- does the vendor maintain a master list of all companies and/or individuals? how many companies and individuals does it cover and what percentage of records have values for each data element?
- can clients import details of vendor-provided data to their own database?

Identity Association

Identity association is the process of linking data from different sources that relates to the same company or individual. It is essential to building a complete view of the customer, which is in turn the foundation of any predictive model. Systems vary substantially in the techniques they apply to this, ranging from relying on the client to identify all links to employing sophisticated techniques to identify certain and probable relationships.

- does the system rely on the client to place an ID on data from different sources that relates to the same company or individual?
- does the system use "fuzzy matches" to link different versions of the same company name or postal address?
- does the system match client data against an external database of known companies or individuals, allowing linkages such as parent/subsidiary or email/postal address?
- does the system link data across different levels such as leads to accounts or opportunities?

Modeling

Few marketers will be interested in the technical details of a predictive analytics system. But it's still important to understand whether the system can build multiple models and how much effort is involved. Building the first model requires connecting to source systems, which can take considerable time. Time to build subsequent models is usually less but still varies widely. You also need to understand how the vendor monitors model performance and the process for updating existing models.

Model Types

- does the system provide predictions at the individual level, company level, or both?
- are individual predictions derived from the company level or are individual predictions built separately?
- is client data always necessary to build a model?
- does the system build a single model for each client or can it build multiple models?
- how does the user specify what the model will predict?

Execution

- how long does it take to create the client's first predictive model? what is done by the client and what is done by the vendor? is there a model training period before the new model is ready to use? how is model performance measured?
- how long does it take to create a new model after the first model? what is done by the client and

what is done by the vendor? -how does the system monitor on-going model performance?

- are existing models updated continuously, as needed, or at regular intervals? can users interfere with the elements of the model to make adjustments?
- how long does it take to update an existing model? -what is done by the client and what is done by the vendor?

Outputs

The types of predictions a system can create impacts which applications it can support. Some systems offer many different types of predictions while others specialize in a single output. You'll also want to understand how the system delivers results to other systems. This is especially important where predictions are used in customer-facing applications such as CRM, Web sites, and marketing automation.

- what types of outcomes can the system predict:
- binary (yes/no, respond/not respond, renew/churn) (note: these are usually accompanied by a probability estimate),
- continuous (value of future purchases),
- categorical (customer segment, preferred content, preferred channel),
- rankings (products most likely to purchase, campaigns most likely to respond to)
- other?
- what scoring output is provided: scores, supporting data, explanations of scores, analytics, other?
- how are outputs made available? (API, batch export, other)
- what prospecting information is provided: names, titles, contact information, company, firmographics, other?
- for which systems are existing connectors available (CRM, marketing automation, Web site, etc.)?
- what is the process to build a custom connector?
- is there an existing end-user interface to access system results, such as viewing scores for an individual prospect or customer?

Other

The functional differences listed in the preceding sections are the most important factors in selecting a system. But vendor attributes also matter. The two most important are cost and the vendor's ability to support your needs in the long term.

Pricing

- how does the vendor structure its pricing?
- are fees based on database size, number of predictions made, number of channels, number of models, etc.?
- are there separate fees for initial set-up?
- are there separate fees for use of the vendor's data and/or third party data?
- are you purchasing a software license or subscribing to a service?
- are there additional charges for professional services?
- is there a long-term contract? what happens if you want to terminate before the contract ends?
- can you set up a trial system? what are the details? what if actual performance doesn't match the trial results?

Vendor

- how long has the vendor been in business?
- how many clients does the vendor have?
- can the vendor provide references with a similar situation to your own?
- what is the vendor's financial position? do they have adequate funding to ensure near-term survival?
- how does the vendor manage deployment and on-going activities to ensure customer success?
- is the vendor's technical infrastructure adequate? How will they scale as their business grows? Are security procedures sufficient and properly documented?

Differences by Application

What you need from a predictive analytics system depends on how you're going to use it. Basic requirements such as accurate predictions and reasonable pricing apply in all situations. Many marketers will want a system that supports multiple applications, saving them the cost and effort of deploying separate products. But even those marketers will have some primary goals in mind and want to be certain that their system supports them well. Here is a brief look at considerations that are more important for specific applications.

- Prospect discovery: the critical requirement is that the vendor provides a rich set of prospects for the client to choose from. This means the primary focus is on vendor data; often, the only client data needed is a list of current customers that the predictive analytics system can use as a seed. In some cases, client data may not even be needed to build a preliminary model for discovery. Prospect discovery systems can work at the company level, so marketers can pay less attention to individual-level data or modeling, although it's useful for the predictive vendor to provide names of individuals with appropriate titles to use as initial contacts. The modeling methods can focus on basic classification (binary or categorical) since the goal is to build a list of likely customers. It can be very helpful to have event identification or trend monitoring capabilities to find prospects whose behaviors suggest they may be just entering the market for the marketer's product.
- Lead scoring: leads are individuals, so individual-level data and predictions are essential. The vendor needs to provide rich details on leads, , since marketers will have little data of their own when a lead first appears. However, there's also a need to incorporate as much client-provided data as possible over time, so scores can be adjusted as leads interact with client systems. This also means that powerful identity association is needed to build a complete profile of interactions across multiple channels, even when the lead does not explicitly identify herself. Models here need to provide continuous outputs so that leads can be ranked effectively.
- Enrichment: advanced matching is again critical so that complete information can be appended to as many individual and company records as possible. Access to

detailed vendor and client data are both important: vendor data adds new information to what the company already knows and client data is essential to building powerful predictions. Since those predictions will often be used to guide interactions across marketing and sales, easy integration with those systems is also a high priority.

- Recommendations: these require access to details of specific content and products each customer has chosen in the past, and preferably those they were offered and didn't choose as well. Categorization and tagging are needed so that larger patterns can emerge, such as interest in different categories or topics. Many recommendations are highly contextual, so the system needs to capture context such as device, channel, and preceding behaviors, and to factor those into its recommendations. High-speed integration with marketing and sales systems is essential to deliver recommendations in real time.
- Lead intelligence: individual and company data are both important, as is monitoring behaviors to generate alerts about which leads require immediate attention. Traditionally, the primary focus has been on internal data reflecting behaviors such as Web site visits, but predictive tools are leveraging social and other external behaviors to provide important clues about lead intentions.
- Customer success: understanding customer satisfaction and identifying problems requires reading data from company service and support systems, including unstructured sources such as telephone notes and Web chat transcripts. These can be supplemented by monitoring external sources such as social media comments and company news releases about investments, acquisitions, new offices, executive changes, and other events. Tracking usage of the company's product is also critical, so the predictive system also needs to import and work with usage data. Alerts based on company events such as executive changes or business news can also trigger the customer success team or account team to reengage to address a new risk or opportunity. Modeling systems need to work with these complex data types to produce multiple models such as churn probabilities and offer recommendations. This all works primarily at the company level although identifying unhappy individuals is also very important. The final key requirement is integration with customer-facing systems.
- Measurement: nearly all key information comes from company systems, including marketing programs and responses, sales automation to track deals, and accounting systems to capture actual revenues. Vendor-provided data may help with some analysis such as segmentation. Advanced identity association is essential to building a complete view of all interactions, although analysis is primarily at the company level. Advanced analytics are needed for sophisticated attribution modeling. Simpler reporting suffices for calculations such as lifetime value and campaign return on investment.

Buying Advice

Selecting a predictive analytics system should follow the same basic process as selecting other systems: start by defining your intended applications and then work backwards to define the tasks needed to deliver those applications, the system features needed to execute those tasks, and the vendors who provide those features. The peculiar characteristic of predictive systems is that some important differences among vendors are nearly impossible to assess in advance, including the utility of their data and the accuracy of their models. This means that selecting predictive systems nearly always includes a test using either historical data or current programs. This will compare vendors against each other and against results without any predictive system. Not all vendors are willing to conduct such tests, although some of the holdouts will offer the alternative of a trial period before signing a long-term contract. Whether you insist on a test will depend largely on whether you feel you have several viable alternatives to compare based on other attributes such as pricing, features, and data coverage. Small firms often skip the test simply because they lack the resources to conduct one, although this is probably a high-risk strategy.

Whether or not you test potential systems, be sure to check references, view demonstrations, and get a clear understanding of pricing and operating policies. Understanding the time and cost to build the first model, the incremental cost of additional models, and the process for rebuilding existing models are especially important for avoiding a choice you'll later regret.

Summary

Predictive analytics can improve a wide range of marketing and sales activities. Vendors differ significantly in terms of the data they provide and analyze, their modeling methods, and the outputs they generate. This paper provides questions to help marketers explore those differences and shows which features are most important for which applications. Using this information, marketers can find the system that best fits their needs and start down the road to predictive marketing success.

About Raab Associates Inc.

Raab Associates Inc. is a consultancy specializing in marketing technology and analytics. Typical engagements include marketing architecture planning, business needs assessment, technology audits, vendor selection, results analysis, and dashboard development. The company also consults with industry vendors on products and marketing strategy

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