Optimizing customer relationships in the era of Big Data

Companies increasingly recognize the value of their customer relationships and the need to continually refine and optimize customer interactions consistently across the enterprise. The use of analytics to understand customers, segment them and target them efficiently has become mainstream.

Now, however, companies face a new and growing challenge – how to fully leverage the benefits of “big data” for increased customer insights without being submerged under a tidal wave of data. With more data from more sources, with an increasing need to include unstructured and semi-structured data in their analysis, and with less time than ever before to respond to changing dynamics and customer needs, companies are seeking new analytic solutions.

In an era of big data, leading companies are recognizing that optimizing customer interactions means optimizing each and every individual customer decision. Delivering optimal customer decisions at the point of contact requires relevance, real-time systems and a focus on recency to use the most current data available.

Successful companies are marryng the power of predictive analytics with the time-tested and proven Decision Management approach to build agile, adaptive and analytic systems. These systems fully leverage big data and advanced analytics to treat every customer right and optimize customer relationships over time.

To compete effectively in this new era of customer-centricity and big data, companies are looking for analytic platforms that can drive these analytics to new heights using all their available data. They are looking for analytic platforms that will let them manage the volume of big data, exploit the variety of big data, and respond to the velocity of big data.
Great customer decisions

At the heart of a good customer relationship is a series of great customer decisions. Every time the customer interacts with the company the right decision has to be made. When is a good time to make a marketing offer and which offer will be best? Should this fee be reversed? How should this customer call be routed given the importance of the customer, the severity of their problem and the available resources? Hundreds, thousands, even millions of decisions every day driving relationships across the customer portfolio.

Great customer decisions are different for every industry but they have three things in common:

- They have **relevance**—they deliver an individually targeted and intensely relevant experience.
- They are **real-time**—they meet the customer’s expectation for immediate response at the point of contact.
- They have **recency**—they reflect everything known about the customer and the customer relationship at the moment of decision.

Relevance

Customers respond to the decisions a company makes about offers, messaging and other interactions as though those decisions were personal and deliberate. When they are not, when they are made without consideration of the customer’s unique profile, companies run the risk of losing business. A focus on relevance means ensuring that offers, pricing and messaging are all based on a complete understanding of the customer and on the company’s relationship with that customer.

Relevance means using information about the customer relationship across all channels in the context of a particular interaction. This involves using information from a customer data warehouse, data in operational systems, data from outside sources as well as what is happening in the company’s systems as customers interact and use their products.

This focus on relevance replaces traditional mass marketing to customers with a strategy that targets a single customer. Old school “macro” decisions about campaigns, segmentation, messaging, pricing, terms and conditions are being replaced with customer-centric “micro” decisions for each specific customer. Everything known about a customer within the company combined with their most recent activities drives an individually targeted and intensely relevant experience.
**Real-time**

The modern consumer has become more accustomed to real-time responses from companies. Their ebook reader downloads a book in seconds, their insurance company allows them to make a claim online and they can get a boarding pass issued right on their smartphone. These customers don’t want to wait days for a response in the mail, be told to come to the branch, or even to be referred to a supervisor in the call center. To focus on real-time means ensuring that the right response to a customer is delivered instantly within their choice of channel.

Real-time means making decisions, responding to requests, handling customer inquiries and approving products in real-time. It means minimizing the time to deliver the products, services and support to a customer at every opportunity. It also means sensing the customer’s needs and identifying opportunities as they occur. Market shifts, external events, competitor campaigns—all must be sensed in real-time.

The outcome of this real-time “sense and respond” approach must be relevant and appropriate. It must take account of location and context so that customers will respond. Suggesting a customer open a new account while they are using SMS to chat with friends is not going to be successful. Real-time sensing combined with understanding of relevance creates situation-based opportunities to better serve a customer.

**Recency**

Companies know their customers, whether the company realizes it or not. Companies have internal data such as account information or products purchased. They have access to demographic and other external data. Increasingly they have access to social media, weblog and other unstructured “Big Data”. All this data is important to understanding customers and their behavior. This data is available to companies as a history of the customer journey. This history has a delay built in as it takes a finite time to record this information and make it available. To optimize the customer relationship, companies need to combine this history with what is happening right now. A focus on recency uses what just happened, what the customer is doing at the moment, where the customer is, in addition to this customer history allows for more effective decisions. For instance, a promotion can take advantage of real-time usage patterns and a customer’s current location and context. Offers at checkout can reflect recent purchases, for example and location.
Decision Management Systems

Traditional marketing and customer management systems struggle to such deliver relevant, real-time, recent decisions. To optimize customer relationships, companies are building agile, analytics and adaptive systems - Decision Management Systems.

Why build Decision Management Systems?

Because managing customer interactions means managing decisions

To optimize customer relationships every decision made about a customer must be relevant, real-time and recent. To take control of these decisions, companies are building Decision Management Systems focused on these customer decisions. These systems act as the decision-making components of an enterprise software Service-Oriented Architecture. They make the decisions that allow channel-specific and other systems to take the most appropriate action for every customer interaction.

Any time the company interacts with a customer there is a decision to be made. To optimize customer relationships, every business process and system needs to be analyzed for interactions. Each customer-facing process has interactions with customers. Managing when and how to make decisions about those interactions allows a company to optimize the relationship across channels and systems.

Managing and improving these decisions is what develops better customer relationships. Delivering consistency across channels and ensuring that the decisions being made are current and timely is critical. Understanding how those decisions are linked to business objectives allows decisions to be made so that the company's relationship with the customer continues to move forward. Making this work means having common components that can be used by multiple systems across multiple channels and delivered to customers through integration with delivery systems such as websites, CRM systems, marketing systems, and more. These components, Decision Services as they are called, are at the heart of a Decision Management System.

What is a Decision Management System?

Agile, analytics, adaptive, focused on decisions

Decision Management is a business discipline and technology stack that builds on existing enterprise applications and IT infrastructure augmented by advanced analytics. Decision Management Systems are built by using this approach to focus on the repeatable, operational decisions that impact individual customers. Once these decisions are discovered and modeled, decision services are built that embody the organization’s preferred decision-making approach in operational software components. The decision-making approach embodied in these components uses
the available data, and analytic insight derived from it, to make the best possible decisions given what is known at the time. The performance of these components, and the impact of this performance on overall organizational performance, is tracked, analyzed and fed back into improving the effectiveness of decision-making.

Unlike traditional information systems, Decision Management Systems are agile, analytic and adaptive.

- They are **agile** so they can be rapidly changed to cope with new regulations, changing consumer preferences or new business conditions.
- They are **analytic**, putting an organization’s data to work, improving the quality and effectiveness of decisions.
- They are **adaptive**, managing experiments and learning from what works and what does not work to continuously improve over time.

Decision Management Systems deliver a high ROI by making the most of every opportunity to interact with a customer, optimizing the relationship and building long term revenue. Decision Management Systems are particularly powerful in their ability to apply analytics, especially predictive analytics, to decisions about customers.

**How to build Decision Management Systems**

To build systems that effectively manage customer decisions you need to follow a three step process—decision discovery, decision services and decision analysis.

- **Decision Discovery.**
  To improve customer decisions you must know what those customer decisions are and what it means to improve them. Decision discovery involves identifying the decisions you make about customers, tying them to your critical business metrics and developing models of these decisions so you understand exactly how you want to make them.

- **Decision Services.**
  Once you know what your critical customer decisions are you can build the decision services at the core of your Decision Management Systems. These services act on all your customer data, applying analytics to power precise, targeted and effective real-time customer treatment across all channels.

- **Decision Analysis.**
  To ensure ongoing improvement in customer relationships, continuous improvement is critical. Decision analysis involves both long-term continuous improvement using experiments and business performance management (building relevance over time) and highly iterative short-term improvements—seeing how well a campaign is performing in real-time so immediate changes to the decisions driving that campaign can be made to maximize its value (leveraging recency).
Big Data Analytics power better customer decisions

At the heart of Decision Management Systems for managing customer decisions are powerful analytic models.

Analytics have real power in customer decisions

Companies that systematically apply predictive analytics to every individual customer decision outperform their competitors. A customer decision is one of hundreds, thousands or maybe hundreds of thousands of similar customer decisions made within a timeframe. These customer decisions determine the actions the company takes in regard to one of its most valuable business assets—a portfolio of customers worth millions or billions in customer lifetime value. The value of each decision is multiplied by the number of customers and the cumulative bottom-line impact is substantial.

Predictive analytic models are critical for determining the optimal action for every individual customer interaction—for making the best decision. Typically, companies begin with predictive analytics by segmenting customers into different groups with similar behaviors and characteristics. The ability to take predictive analytics beyond big “buckets” is a watershed moment in customer relationship development. Successful companies are using these techniques to develop much more granular segmentation for more precise targeting.

Predictive analytic models that predict the likely future behavior (“propensity”) or value of customers are also widely used. Using predictive analytic techniques to develop models that will score the likelihood that a particular customer is a retention risk or that a particular offer will be accepted puts the data that companies have about their customers to work. These predictions can also be used in segmentation models—using the retention or churn risk, for instance, as one of the criteria for membership in a customer segment.

Given the wide range of product offers and actions that must be optimized, very large numbers of predictive analytic models may be required—100s or 1000s of propensity models (one for each offer or product) are not uncommon. These models allow each potential action to be considered based on its probability of acceptance. Real-time scoring can be applied to incorporate up-to-the-minute information about the customer to ensure predictions are as accurate as possible.

Companies are using Big Data to drive analytics

Companies that marry the power of predictive analytics with a 360 degree view of the customer create a powerful combination. The era of Big Data is an opportunity for companies to enrich their operational data with demographic, social, other third-
party data and web analytic data to better understand customers and prospects. By pulling in all the available data into the predictive modeling process, big data improves the interaction with the customer—driving more effective predictions that improve each individual customer decision.

**Using Big Data for analytics has challenges**

Using Big Data to improve customer decisions is a great opportunity but it also involves an explosion in data complexity. This complexity creates a set of challenges for those developing customer analytics. Big Data is often defined as data that has Volume, Velocity and Variety. Each characteristic creates its own challenges.

**Volume**

Big Data creates a volume challenge because companies are analyzing more records as they move into a Big Data era. More records means more storage, it means greater performance challenges and it means either processing more records to build analytics or effective (and complex) sampling techniques must be used to manage this volume.

**Variety**

Big Data means more data sources with more data fields available for analytics. This massively increased number of fields must be managed and fed effectively into your predictive analytic models. These data sources are also more varied—many of the new data sources being tackled are unstructured, such as text from call center notes or social media, and others are semi-structured such as weblogs and sensor data. These new sources require new analytic techniques as well as integration with the more traditional data sources such as CRM data that are at the heart of most good analytic models about customers. This variety also exacerbates the challenges of volume as analyzing unstructured data sources often results in yet more attributes. For instance, analysis of social media might result in an additional field for the number of times a customer makes a positive statement about your product.

**Velocity**

Finally, Big Data has high velocity—it is often rapidly changing, creating a need to flow data rapidly into analytic modeling. The time it takes to store and snapshot data for analytics can be critical in determining how accurate a model will be. In addition, with companies needing to make more decisions about customers in real-time, deploying and executing analytic models must also happen faster. Batch scoring and leisurely updates of analytic models don’t work well in a fast moving Big Data environment.
Meeting the challenges of Big Data Analytics

Big Data is changing what a 360 degree view of the customer means with new kinds of data, many new data sources, rapidly changing data and large volumes. Velocity, Volume and Variety are the three challenges of Big Data. To optimize the customer relationship using analytics, these challenges must be met. Meeting these new challenges cannot require a completely new infrastructure—there should not be one infrastructure for “old” or “little” data and another for Big Data. Companies must evolve a data and analytic infrastructure that will manage the volume of Big Data, exploit the variety of Big Data and respond to the velocity of Big Data.

Manage Volume

To manage volume, your data and analytic infrastructure must support both breadth and depth of data: breadth in terms of the number of customer attributes or properties involved and depth in terms of the number of records involved.

Integrating multiple Big Data sources with internal data can result in huge numbers of attributes or properties. When you start developing predictive analytic models to this dataset you will create large numbers of derived characteristics to drive these models. For instance you might want to derive the number of times in the last 90 days that a customer has purchased a product and then used the “Tweet this” button to say something positive about it.

Each such derived characteristic has to be handled by the analytic infrastructure to drive models - this means analytic algorithms, especially machine learning algorithms that can support thousands of properties and can sift them to find the ones that are highly predictive without lots of manual intervention. It also means tools that can generate all the possible combinations—positive comments in the last 30, 60, 90, or 120 days for instance—so you can see which timeframe is going to be most effective.

You also need data storage for all these properties. If you can easily store tens of thousands of columns then you can:

- Use these properties to build predictive analytic models.
- Make these same properties available to reporting and query tools.
- Ensure that the operational infrastructure will be able to feed these properties into any model that needs them in real time.

Making sure all these properties are available in all three environments is critical. It lets business people report using the properties that the analytics team identifies as highly predictive and that get built into the model. At the same time it ensures that the CRM system or the website can access those same properties to score a customer in real-time.
Besides supporting the breadth of data, you also need to support depth of data—large numbers of records. Predictive analytic techniques generally work best with more data so that, for instance, seasonality and rare corner cases show up in the data. Managing and delivering large amounts of data to analytic algorithms has historically been difficult leading to modelers using data samples. There’s nothing wrong with sampling if it is done right but it’s one more relatively complicated step so if your analytic infrastructure can handle the volume without sampling, so much the better. This means pushing lots of data through, taking advantage of in-memory and multi-core/multi-threaded approaches and tightly integrating with the data storage infrastructure to minimize data movement. Data storage can help too with intelligent compression of data that varies by data type and column so that less I/O is required and so more data can be stored in the “live” data infrastructure.

**Exploit Variety**

Big Data comes in a much wider range of formats than traditional enterprise data sources. This new data requires new kinds of fields and formats that need to be accessed at volume, at scale and at speed. Unstructured and semi-structured data need to be given structured meaning so they can be used in predictive analytic models and this process creates new properties and information as techniques like entity extraction and sentiment analysis are applied. Analysis of these new columns means that the number of properties or columns can increase rapidly.

To exploit this variety you need to be able to derive new facts from structured data, semi-structured data and unstructured data. Entity extraction and other kinds of text analytics are critical and must be applied rapidly and effectively to very large amounts of data. Text analytics has exploded in recent years with better support for the meaning of text and sentiment analysis as well as entity extraction and a wide variety of robust techniques is essential to maximize the value of these data sources.

The integration of results from these techniques with more traditional structured data so that the combined data set can be used to build derived attributes and predictive analytic models is key. It is not enough to have separate environments for these two kinds of analysis; they must be brought together to focus on analytics that improve customer decisions. As noted above, these new customer facts should also be integrated into the reporting and development environment seamlessly for a coherent and consistent view of the customer.

**Respond to Velocity**

Big Data has velocity both because new data arrives rapidly and continuously and because the structure or content of that data changes. A suitable infrastructure allows you to respond to both kinds of changes. It should be possible to dynamically add or remove columns in the data infrastructure to reflect ongoing changes in data.
structure or new analysis techniques without a serious impact on other columns or on activities being carried on in parallel. This kind of structural agility allows data sources to change and to come and go as necessary. A similar tolerance for new and changed columns is desirable in the analytic infrastructure also so that models can be built and re-built using the most appropriate and available properties at any moment.

The velocity with which new data arrives is also important. Data infrastructure that can support data streaming in continuously and rapidly integrate that data with historical data already stored is ideal, rather than having to wait for batch updates. Being able to generate inputs to analytic modeling techniques automatically and to schedule new modeling activities to see if the arriving data has changed the model helps ensure that the analytics too reflect the most recent data.

Velocity also comes up in deploying the results of analytics. Just as the velocity of data has changed, so has the velocity of business. Organizations cannot wait as long to use analytic results and cannot afford to spend a long time deploying analytic models. An analytic infrastructure that supports rapid and automated deployment of predictive analytic models both to the data infrastructure for in-database scoring and to operational environments for real-time scoring helps ensure that the customer decisions that matter are being driven by up to the minute analytics.
Conclusion

Companies from retail to travel, insurance to banking are focusing increasingly on customers and on improving customer interactions. With customers looking for relevant, real-time interactions based on their most recent activities, companies are turning to a new class of system. These Decision Management Systems are agile so they can cope with changing circumstances, analytic to make maximum use of Big Data and adaptive to improve over time. Analytics are at the heart of these systems and drive better customer decisions throughout the lifecycle and across channels and systems. Big Data can and will improve those analytics provided companies can cope with the volume, variety and velocity inherent in Big Data.

What is needed today is a data and analytic infrastructure that manages this volume, both in terms of breadth and depth; that allows analytic teams to exploit the rich variety of data available; and that responds effectively to the velocity with which new data arrives and existing data changes.

Contact Us

If you have any questions about Decision Management Solutions or would like to discuss engaging us we would love to hear from you. Email works best but feel free to use any of the methods below.

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