FROM DATA COLLECTION TO BEHAVIOR PREDICTION: WHAT IS AFTER BIG DATA AND SMALL DATA? PREDICTIVE MARKETING AND THE PATH TO SUCCESSFUL BUSINESS

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Abstract. *The latest technologies, together with the fast growing access to Internet and the constant innovation in this field (mobile applications, wearable gadgets, sensor technology) are transforming the economy and the society per se on a scale never seen before, offering opportunities for new forms of social interaction and innovative personalized services. For marketers, this means that tools and strategies that were considered as cutting-edge, are quickly becoming obsolete, requiring an equally fast adoption and adaptation to the new tech environment. The present paper is an exploratory intercession in the way marketers can extract intelligence from big data and small data in order to better map their strategy, predict future outcomes, map in a more accurate manner the persons with the highest propensity to become your customers, highly personalize messages and complement the bigger picture analysis of the role of different media. From this point of view, the authors focus shifts towards the way predictive marketing is gaining momentum and has an impact in the way marketers and new business owners can identify what values and goals guide their brand strategy, what drives performance for their business and what structures, tools, and working methods will enhance a purposeful positioning of their brand.*

Keywords*: big data; predictive marketing; digital; small data; customer; predictive analytics.*

What is next after gathering data

'The big data revolution is upon us state LaRiviere et al. (2016), while Boyd and Crawford (2012), Tene and Polonetsky (2013) strengthen it by underlying that we live in the age of big data. LaRiviere et al. (2016) affirm that survey-based reports find that firms are currently spending an estimate of $36 billion on storage and infrastructure, and that is expected to double by 2020. According to IBM, humans create 2.5 quintillion bytes of data. In fact, 90% of the world's data has been created in the last two years. The constant usage of the Internet and the advent of technological innovations, the amount of data available about the customers becomes limitless.

Prior to 2008, data was rarely considered in terms of being small or big, observes Kitchin and Lauriault (2014). The authors point out that all data was, in effect, what is now sometimes referred to, as small data, regardless of their volume. Due to factors such as cost, resourcing, and the difficulties of generating, processing, analyzing and storing data, limited volumes of high-quality data were produced through carefully designed studies, using sampling frameworks designed to ensure representativeness.

When analyzing big data, there are a few characteristics that emerge:
- huge in volume (terabytes or petabytes of data)
- high in velocity, being created in or near real-time
- diverse in variety and type (structured/unstructured in nature, often temporally and spatially referenced)
- exhaustive in scope, striving to capture entire populations or systems (n=all);
- fine-grained in resolution, aiming to be as detailed as possible, and uniquely indexical in the identification
- relational in nature, containing common fields that enable the conjoining of different data sets
- flexible, holding the traits of extensionality (can add new fields easily) and scalability (can expand in size rapidly) (Dodge & Kitchin, 2005; Boyd & Crawford, 2012; Marz & Warren, 2012; Mayer-Schonberger & Cukier, 2013; Kitchin, 2013).

The benefits of big data can be identified in a range of sectors, both large scale and small firms: the ability to analyze operational and transactional data, to glean insights into the behavior of online customers, to bring new and exceedingly complex products to market, and to derive deeper understanding from machines and devices within organizations (Vesset & Morris, 2013). For example:
- Technology companies are using big data to analyze millions of voice sample to deliver more reliable and accurate voice interfaces
- Banks are using big data techniques to improve fraud detection
- Healthcare providers are leveraging more detailed data to improve patient treatment
- Manufacturers are using it to improve warranty management, equipment monitoring, optimizing the logistics of getting their products to market
- Retailers are harnessing a wide range of customer interactions, both online and offline, in order to provide more tailored recommendations and optimal pricing (Vesset & Morris, 2013).

The term big then is somewhat misleading as big data is characterized by much more than volume, notes Kitchin (2014). The author details that some 'small' datasets can be very large in size, such as national censuses, that also seek to be exhaustive and have strong resolution and relationality. However, Kitchin (2014) specifies that census datasets lack velocity (usually conducted once every 10 years), variety (usually c.30 structured questions), and flexibility (once a census is set and is being administered it is all but impossible to tweak the questions or add new questions or remove others and generally the fields are fixed, typically across censuses, to enable time-series analysis.

Podesta et al. (2014) affirm that one of the most intensely discussed areas of big data analytics to date has been in the online advertising industry. It is used to serve customized advertisements as people browse the web or travel around town with their mobile phone. However, the information collected and the uses to which it is put, are far broader and quickly changing with data derived from the real world increasingly being combined with data drawn from online activity.

The authors note that the end result is a massive increase in the amount of intimate information compiled about individuals. This information is highly valuable to businesses of all kinds. It is bought, bartered, traded, and sold. Analyzing and using big data is challenging and sometimes questionable (Crișan, Zbuchea, & Moraru, 2014). An entire industry now exists to commoditize the conclusions drawn from that data. Products sold on the market today include dozens of consumer scores on particular individuals that describe attributes, propensities, degrees of social influence over others, financial habits, household wealth, and even suitability as a tenant, job security, and frailty. While some of these scoring efforts are highly regulated, other uses of data are not.

LaRiviere et al.'s (2016) question is what is next after gathering big data. Looking at the current marketing stage, the answer is very close and their answer might be: the first use case involves predicting demand for consumer products that are in the "long tail" of consumption. Firms value accurate demand forecasts because inventory is expensive to keep on shelves and stockout are detrimental to both short-term revenue and long-term customer engagement. Aggregated total sales are a poor proxy because firms need to distribute inventory geographically, necessitating hyperlocal forecasts. The traditional way of solving this problem is using time-series econometrics with historical sales data. This method works well for popular products in large regions but tends to fail when data gets thin because random noise overwhelms the underlying signal. A big data solution to this problem is to use anonymized and aggregated web search or sentiment data linked to each store's location on top of the existing time-series data.

In their book, The only rule is it Has to work, Ben Lindberg and Sam Miller, tell the true story of how they tried to bring sabermetric1 superiority to the Sonoma Stompers, a minor league baseball team from California. Inspired by the Moneyball2 theory, the authors brought predictive analytics in the team. Scharge (2016) analyses their endeavor and notes that persuading teams to embrace statistics they do not really understand makes a nifty tale of data-driven despair. Getting people to consistently and reliably act upon real data is a real leadership challenge. Scharge, in dialogue with Lindberg, found out that predictive analytics creates organizational winners and losers, not just insights. In their words, competitive organizations want results and players are not just supposed to play well; they are expected to win.

The author remarks that predictive analytics explicitly seek to pick winners, sideline losers, and manage risk. That makes them as much a source of power as insight. Serious analysts know their numbers will influence who plays, who is seen to have potential, and who gets cut. The players know this, too. However, who really benefits when analyst and their spreadsheets gain power? Machiavelli proves a better guide than mathematics. Lindberg acknowledges that the players they have signed had a

[1] Sabermetrics is the empirical analysis of baseball, especially baseball statistics that measure in-game activity. The term is derived from the acronym SABR, which stands for the Society for American Baseball Research

[2] Moneyball: The Art of Winning an Unfair Game is a book by Michael Lewis, published in 2003, about the Oakland Athletics baseball team and its general manager Billy Beane. Its focus is the team's analytical, sabermetric approach to assembling a competitive baseball team, despite Oakland's disadvantaged revenue situation. A film based on the book was released in 2011.

natural allegiance to them because they were only there because of their spreadsheets and their stats.
Moreover, Lindenberg and Miller (2016) say that the players were more open to data-driven suggestion not because they necessarily bought into Moneyball metrics, but out of gratitude and loyalty. On the one hand, Lindenberg and Miller (2016) observe, leveraged limited information to target undervalued talent. On the other hand, what wasn't being measured - self-motivation, team chemistry, manager/player compliance with statistical insight - had great importance as well. From this perspective, Scharge affirms that the more analytics become, the more imperative it is to measure their impact and influence. In other words, metalytics - analyzing the analytics - define how quants gain insights into how they create insights, as well as how effective they prove at communicating them.

Predictive analytics is applied in various domains, including analyzing a person's individual propensity to criminal activity (Podesta et al., 2014). For example, Podesta et al. (2014) mention that in response to an epidemic of gang-related murders, the city of Chicago conducted a pilot that shifts the focus of predictive policing from geographical factors to identity. By drawing on police and other data and applying social network analysis, the Chicago police department assembled a list of roughly 400 individuals identified by certain factors as likely to be involved in violent crime. As a result, police have a heightened awareness of particular individuals that might reflect factors beyond charges and convictions that are part of the public record.

Gregersen (2013) considers that a new approach to analysis, called catalytic questioning, is offering business leaders fresh insights about their market. The author explains that catalytic questioning is an alternative to brainstorming whereby the team can do question-centric work. They pick a problem that the team cares deeply about and ask nothing but questions (no answers allowed) until they reach at least 50. After this process, they should take a step back and determine three or four questions that are the most "catalytic" – the startling ones that force the team to change your perspective. After this, the team must seek solutions to these questions until they uncover extraordinary insights and answers.

An example, in this sense, is a major transportation company that was struggling to understand what was impacting its financial performance and to predict where the market was heading. Using catalytic questioning, SAP, who offers software and technology solutions for business, brainstormed with executives. From the questions, the data scientists developed forecasting models to analyze more than 48,000 combinations of "products shipped x location x customer" that were validated against thousands of macroeconomic factors, competitive data, and customer sentiment. Fueled by uncommon questions and big data, the company in the case is now predicting future outcomes and competing more successfully.

Anticipating customer needs is not a new concept, Antun and Levin (2015) stress out. The authors develop that what is new is the ability to anticipate and respond to customer needs automatically, near real time and at a large scale, for hundreds, or even millions of customers at a time. Following this path, the promise of predicts marketing is to bring the personal relationships of the corner store to the modern world of offline and online marketing.

Research methodology

The research methodology adopted by the authors is based on descriptive research based on empirical data from secondary sources. The main purpose of the paper is to map the means in which companies are incorporating Big Data and predictive analytics with their traditional research and marketing tools. Moreover, the authors' aim is also to better understand how organizations are using this concept to apply their marketing strategy. The paper is setting a baseline for future in-depth analytical research.

Predictive marketing

Applications and websites were the first personal data collectors. Podesta et al. (2014) detail that by tracking users' activities online, marketers could deliver targeted advertising and content. More recently, intelligent technology in physical products has allowed companies in many industries to collect new types of information, including users' locations and behavior. The personalization this data allows, such as constant adaptation to users' preferences, has become central to the product experience. (Google's Nest thermostat, for example, autonomously adjusts heating and cooling as it learns homeowners' habits.)

In their study Why Modern B2B Marketers Need Predictive Marketing, Raab Associates reflect that marketers have used predictive modeling for decades. Applications such as response models and media mix optimization have reliably produced 20 to 30% improvements in return on investment. Yet, valuable as they are, these benefits have been marginal improvements in core marketing operations. On one side, according to the study, marketers could achieve acceptable results using manual techniques or doing without them altogether. On the other side, they note that this is not the case in other applications. Fraud detection during credit card transactions, for example, is only possible using predictive models to identify questionable behaviors in real time. Human analysts could not react quickly enough to intervene as the interactions occur. Similarly, online merchants like Amazon.com gain essential profits from instant, personalized product recommendations based on predictive analytics. Airlines are critically dependent on yield optimization systems that adjust prices to fill seats as profitably as possible.

The rich new streams of data have also made it possible to tackle complex challenges in fields such as health care, environmental protection, and urban planning. For example, Medtronic's digital blood-glucose meter is connected through wireless sensors to a device that alerts patients and health care providers that blood-glucose levels are nearing troubling thresholds, allowing preemptive treatments. Moreover, the car service Uber has recently agreed to share ride-pattern data with Boston officials so that the city can improve transportation planning and prioritize road maintenance. These and countless other applications are increasing the power and value of personal data (Podesta et al., 2014). Predictive marketing is the practice of extracting information from existing customer data sets to determine a pattern and predict future outcomes and trends (Everstring, 2015, The State Report of Predictive Marketing Survey Report). More specifically, it relies on using data to make more business wise marketing decisions by predicting which marketing activities are more likely to be successful and which one are more likely not to be.

Practitioners like Brian Kardon, Chief Marketing Officer (CMO) Lattice Engines and member of top 10 global CMO Global top for companies with more than 250 million revenue, says that predictive marketing works by taking all the data about contacts and accounts in the world – from both internal (e.g. CRM, marketing automation) and external (e.g. blogs, websites, government sites, social media channels) sources and applying modern data science to solve marketers' top challenges – Who is going to be my next customers? How do I convert them? How can I find more of these ideal customers? etc.

There are several ways in which predictive marketing is correlated with the data a company has. Predictive analytics is applied in many ways to help businesses overcome a plethora of challenges. The core difference in one mode of application to another is what's being predicted. Predicting customer response, click, or defection are each very different things, and deliver business value in different ways (Siegel, 2016). In Gartner's (2011) framework, the predictive marketing relies on a continuum of analytics capabilities: descriptive (what happened), diagnostic (why it happened), predictive (what will happen) and prescriptive (what to do next). In the marketing field, predictive capabilities can help professionals to forecast with an acceptable level of reliability what customers are the best fit for them and for the business so the marketer can take the appropriate actions to convert them into buying customers more effectively.

More concretely, predictive marketing, with the inclusion of advanced data science is offering the possibility to marketers to make smarter decisions based on the actions buyers actually taken and by layering data models over marketing strategies marketers can have more insight than ever before into their pipeline (Everstring, 2015) Predictive analytics plays a big role in giving businesses the edge to stay competitive despite the rapid changes in the digital landscape.

According to the specialists at Forrester, predictive marketing is related to data services in general. They divide the data providers into three categories: data aggregators (collect and append general business data like contact info), data enrichers (collect and enrich marketing and sales activity data with insights relevant to the marketing process), predictive modelers (apply mathematical algorithms to the data to match patterns to best-fit criteria).

Many companies use predictive marketing to forecast content performance to give their brand adaptive recommendations. This way, they can analyze their audience's engagement patterns and the content produced. Moreover, predictive marketing can provide valuable information for the sales team, for example, what customers are likely to convert based on the behavior of the application used.

Siegle (2016) believes that the "magic" of predictive analytics is in how the valuable segments are discovered. The optimal segment is often arcane and involved, the kind of esoteric combination of features one would expect only a computer to uncover. Core

predictive modeling methods do this very well by crunching historical data, thus learning from the collective experience of your organization.
Studies like shows that How Predictive Marketing Analytics Boosts B2B Business Performance show that 89% of marketers have predictive analytics on their roadmap for 2016. The same report determines that 49% of marketers are using predictive analytics today and 40% plan to implement analytics in the next 12 months. The additional information identifies that 78% of marketers see their prospects' buying journeys becoming more complex and nonlinear. 80% of survey respondents agreed that buyers are increasingly going online to educate themselves about products and services.

In what concerns the challenges faced by the marketers, they need to ensure the data quality and to manage data from a verity of sources (47%), as they attempt to have more accurate and greater insights about customers and prospects. Less of the marketers interviewed (36%) face the challenge of managing the velocity of data generation, one of the foundational elements of big data definitions industry-wide by Gartner and other research firms.

Table 1. Business Applications of Predictive Analytics (Siegel, 2016)

Business application:	**What is predicted:**
Customer retention	customer defection/churn/attrition
Direct marketing	customer response
Product recommendations	what each customer wants/likes
Behavior-based advertising	which ad customer will click on
Email targeting	which message customer will respond to
Credit scoring	debtor risk
Fundraising for nonprofits	donation amount
Insurance pricing and selection	applicant response, insured the risk

Applied predictive marketing

According to a survey produced by Econsultancy (2016), in which analysts were trying to state the most important characteristic to establish a "digital culture", 58% of the respondents mentioned the capability of being customer centric oriented and 48% data driven. MacDonald (2016) appreciates that the correlation between the two characteristics and the consequential usage leads to unveiling the real potential of customer value and its lifetime (CLV) in order to produce relevant results from predictive marketing and its techniques.

Carolyn Taylor, CEO and author of 'Walking the talk: building a culture for success (2005)', states customer centricity as one of six archetypes for building a successful business organization. Zappos retail has implemented its business concept combining the benefit of gathering data being customer centric oriented and redefining also the managing system from Hierarchy to Holacracy (self-management approach) under the leadership of Tony Hsieh (CEO). According to an article published by the American Enterprise Institute over the Fortune 500 firms in 1955 vs 2014, 88% of them failed due to an internal organization, structure and business culture. Laloux (2015) in his book reinventing organizations describes these dynamics as "Tail" organizations.

Companies like Amazon, Facebook, and Netflix have been pioneering the use of algorithms and predictive marketing to engage their customers, increase sales and advertising efficiency. And not only them: companies from domains like telecommunication, financial services, and gaming industries, use predictive marketing to change both business and consumer marketing across the customer lifecycle (Antun & Levin, 2015).

Netflix is one of the most notorious companies to use predictive marketing. With a team of 800 engineers, they use data to get more engagement with their content. Marr (2015) recalls that their efforts here began back in 2006 when the company was still primarily a DVD-mailing business (streaming began a year later). In 2009, the company offered 1 million dollars to a team or an individual that would improve its recommendations algorithms. The prize was given to a team of scientists that improved the algorithm by a little more than 10%.

At first, Marr (2015) noted that analysts were limited by the lack of information they had on their customers – only four data points (customer ID, movie ID, rating and the date that the movie was watched) were available for analysis. As soon as streaming became the primarily delivery method, many new data points on their customers became accessible. Data, such as time of day that movies are watched, time spent selecting movies and how often playback was stopped (either by the user or due to network limitations) all became measurable. Effects that this had on viewers' enjoyment (based on ratings given to movies) could be observed, and models built to predict the "perfect storm" situation of customers consistently being served with movies they will enjoy. Moreover, Netflix ran only in 2015 160 A/B tests, primarily on new customers, each comparing between two and 20 different experiences. Since most of Netflix's new customers are international and have been for some time, its UI already acts as a global common denominator (Barett, 2016).

In order to launch one of their most famous series, House of Cards, Netflix has used data from all the 27 million subscribers from the United States. Based on the information, they could observe that movies directed by David Fincher, the director of "The Social Network", were watched from beginning to end (Shama, 2015). This was not the only information they took into consideration. Based on the big data and small data, Shama (2015) notes, Netflix identified Kevin Spacey as one of the most popular actors, while the British version of "House of Cards" was a very well-received mini-series in the United Kingdom.

Barett (2016) highlights that Netflix has a well-earned reputation for using the information it gleans about its customers to drive everything from the look of the service to the shows in which it invests. He describes the process: Netflix assigns each subscriber three to five of these clusters, weighted by the degree to which each matches their taste. For all the thousands of titles in the company's catalog, the average member only sees 40 to 50 options in a typical visit. Clusters, which can comprise anywhere from tens of thousands to millions of subscribers, are what help ensure that those members see the right 40 to 50. The viewers are not limited strictly to your cluster assignments, as the algorithm occasionally offers glimpses outside the silo.

Shama (2015) gives another pioneering example in what concerns the predictive marketing: Amazon. As the author remarks, Amazon is offering a recommendation for products and services to their users taking into consideration their past behavior. Antun and Levin (2015) mention that predictive analytics was a practice the company has installed since their beginning. This way, recommendations that appear under a product a potential buyer is considering of adding in her cart, is part of what makes Amazon such an e-commerce powerhouse today. The same authors mention that the company has stated publicly that 35% percent of its sales come from recommendations made by their predictive engineers, which would equate USD $25 billion of revenue in 2013. The company is using predictive analytics in many other ways too, such as predicting what email newsletter to send to you, or to nudge you to at the right times to reorder an item.

Rijmenam (2016) determines that Amazon uses Big Data to monitor, track and secure its 1.5 billion items in its retail store that are laying around it 200 fulfillment centers around the world. The author mentions that Amazon stores the product catalog data in S3, a simple web service interface that can be used to store any amount of data, at any time, from anywhere on the web. It can write, read and delete objects up to 5 TB of data each. The catalog stored in S3 receives more than 50 million updates a week and every 30 minutes all data received is crunched and reported back to the different warehouses and the website. Kharabanda (2010) gives another example: one application of their predictive analytics is that every time a signed up user is purchasing a product from the Amazon platform, the purchase will be saved and memorized on a specific server that will create a profile for that specific user. As soon as profile has been created this person will obtain recommendations that refer to the recently purchased product on Amazon.

Other industries benefit from starting using predictive marketing. Companies in the field of personal matching like match.com, OkCupid, Tinder and Badoo are using the predictive marketing at its best. How do they model and predict human attraction? By using a series of tools like Synapse to predict customers' behaviors. Amazon, Netflix, and Pandora3 are using the same tool to recommend new products, movies or songs based on a user's preferences. In addition, in order to gather data, match.com is using chemistry.com to do personalized surveys and get exhaustive data about their users, turning then to predictive analytics.

Mavi, a jeans and apparel brand retailer has successfully used the predictive marketing program to level up their sales and brand awareness. Omer and Levin (2015) note that Mavi acquired a cloud-based predictive marketing solution in 2009. This decision allowed the company to consolidate, clean and de-dupe their customer data on a daily basis. After this step, they were able to start using data gathered to make hypersonalized campaigns. The authors give the following example of the use of

[3] Pandora Internet Radio is a music streaming and automated music recommendation service powered by the Music Genome Project.

predictive marketing: the company has used predictive analytics to find groups of people with distinct product preferences - product-based clusters. They identified at least three different clusters: customers who favored mostly woven shirts, customers who favored beachwear, and customers who were more inclined to high fashion. Having the data, Mavi has launched a reengagement campaign for lapsed customers and managed to reactivate 20% of them.

Conclusions

The question, 'What's next after big data' is more than legit. As more and more companies shift the data, the benefits generated by the combination and interaction of gathering data, analysis, customer value, internal structure are coming to the surface.

In this preliminary research, the intention of the authors consisted in analyzing the shifts in the conversation regarding gathering data and the practical use of the data for marketing purposes. The need for a customer-centric approach has always been present in the marketing strategy. Predictive marketing is bringing more valuable results to companies, by better understanding the customer data and the potential to provide customized content. The personalized content equates to a higher retention rate, reduced attrition rate, and knowing what the customer want before they even know it.

The impact of predictive marketing and its digital tools on companies' activities finds also a reflection on setting and re-implementing budgets for the execution of these. A study performed by Mondo (2016) called "The Future of Digital Marketing", in which 262 marketing executives (B2B/B2C) have been interviewed, shows that 80% of the companies will increase their digital marketing budgets over the next year despite the modest 3.2% global economy growth (IMF, 2016).

Companies like IBM have recently invested in predictive risk analytic modeling with the aim of gathering big data in order to avoid or mitigate risk events and consequentially enhance the efficiency of the operation. Thus the benefit of having predictive intelligence combined with the identification of the customers DNA, sees multiple scenarios of its usage defining almost in real time new audience/market' trends and insights.

Furthermore, local research would surely bring a better rate of understanding of how local companies are using predictive marketing, especially small to medium size.

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