The Power of Social Media Analytics

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Unveiling the Power of Social Media Analytics

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Introduction

With more than 4,100 properties in over 90 countries, Accor Hospitality was facing pressure to increase customer satisfaction and quality of service in the midst of an economic downturn. To handle the situation, it turned to Synthesio, a global, multi-lingual social media monitoring and research company, to examine the more than 5,000 customer opinions that are posted about Accor's various brands each month on travel sites. Accor saw its main challenge as being able to quickly identify customer dissatisfaction and then correct problems at their source. Synthesio created a tool specially designed to track the online reputation of 12,000 hotels, including both Accor's and its competitors'. It quickly revealed a number of problems that Accor's customers were experiencing. For example, room keys were being de-magnetized by customers' smart phones. Accor was then able to work with its room key supplier to quickly fix the problem. On top of this, Accor was able to set up a rewards and training program that encouraged individual hotels to connect with customers through online conversations. Within one year of hiring Synthesio, the Novotel brand within the Accor group experienced 55% growth in positive feedback in online posts as well as a huge decrease in the number of negative comments.

Social media analytics "is concerned with developing and evaluating informatics tools and frameworks to collect, monitor, analyze, summarize, and visualize social media data … to facilit[ate] conversations and interactions … to extract useful patterns and intelligence…"[28]. The Accor example illustrates how social media analytics can help businesses. The ubiquity of smart phones and other mobile devices, Facebook and YouTube channels devoted to companies and products, and hashtags that make it easier to instantly and broadly share experiences all combine to create a social media landscape that is rapidly growing and becoming ever more part of the fabric of businesses. As the number of users on social media sites continues to increase, so does the need for businesses to monitor and utilize these sites to their benefit.

In the remainder of this paper, we explore how the explosion in social media necessitates the use of social media analytics; we explain the underlying stages of the social media analytics process; we describe the most common social media analytic techniques in use; and we discuss the ways in which social media analytics create business value.

The Need for Social Media Analytics

In the early days of social media, PR agencies would monitor customers' posts on a business's own website in an attempt to identify and manage disgruntled customers. With the explosion in the number of social media sites and the volume of use on them, this is not nearly enough. Consider the prevalence of social media[1]:

[1] We present throughout the paper statistics obtained from a number of websites that closely track such issues, including: adweek.com, alexa.com, internetworldstats.com, comscore.com. We obtained additional statistics from social media sites themselves.

- Social networking is the most popular online activity
- 91% of online adults use social media regularly
- Facebook, YouTube, and Twitter are the first, third, and tenth most-trafficked sites on the Internet

But even these statistics fail to provide a full account of the influence that social media are having. Users spend more than 20% of their time online on social media sites. Facebook alone has a *worldwide* market penetration rate above 12%; in North America it is 50% . These rates are growing quickly, with Facebook alone gaining 170 million new users between the first quarter of 2011 and the first quarter of 2012, an increase of 25%. Mobile use of Facebook is growing even faster, at a 67% annual clip.

The amount of information seen during a single day gives a more startling indication of social media's enormous influence. Facebook's nearly one billion active users collectively spend approximately 20,000 *years* online every single day. In the same twenty-four hour period, YouTube has over 4 billion views, amounting to 500 years of video (spread among 800 million unique users), and 140 million active Twitter users send out more than 340 million tweets.

Importantly, these are not simply passive uses of social media. YouTube's analysis of its videos indicates 100 million people take some sort of "social action" every week (by liking, disliking, commenting, etc.). These actions doubled in the span of two years. Facebook now integrates social actions in its online ads, for instance by allowing users to see if their friends have liked or voted on products being advertised. Similarly, hashtags on Twitter (and now other social media platforms) have given users another quick and easy way to express their likes, dislikes, interests, and concerns, and these present further opportunities (or challenges) to businesses that want to stay abreast of these sentiments.

The Social Media Analytics Process

Social media analytics involves a three-stage process: *capture*, *understand*, and *present*. (See Figure 1). The *capture* stage involves obtaining relevant social media data by monitoring or "listening" to various social media sources, archiving relevant data and extracting pertinent information. This process can either be done by a company itself or through a third-party vendor. Not all data that are captured will be useful. The *understand* stage selects relevant data for modeling, removes noisy, low quality data, and employs various advanced data analytic methods to analyze the data retained and gain insights from it. The *present* stage deals with displaying findings from Stage 2 in a meaningful way. Our framework is derived from familiar, broadly applied input-process-output models, and is consistent with the approach of Zeng et al. [28], whose *monitor* and *analyze* activities are subsumed by our *understand* stage; and whose *summarize* and *visualize* activities fall under our *present* stage.

There is some overlap among these stages. For instance, the *understand* stage creates models that can help in the *capture* stage. Likewise, visual analytics support human judgments that complement the *understand* stage as well as assist in the *present* stage. These stages are conducted in an ongoing, iterative matter rather than strictly linearly. If the models in the *understand* stage fail to uncover useful patterns, they may be improved by capturing additional data to increase their predictive power. Similarly, if presented results are not interesting or have low predictive power, it may be necessary to return to the *understand* or *capture* stages to adjust the data or tune the parameters used in analytics. A system supporting social media analytics may go through several iterations before it becomes truly useful. Data analysts and statisticians help develop and test systems before they are used by others.

Stage 1: Capture

For a business engaged in social media analytics, the capture stage allows it to identify conversations on social media platforms related to its activities and interests. This is done by collecting massive amounts of relevant data across hundreds or thousands of social media sources using news feeds, APIs, or by crawling. The capture phase covers popular platforms such as Facebook, Twitter, LinkedIn, YouTube, Pinterest, Google +, Tumblr, Foursquare, etc. as well as smaller, more specialized sources such as Internet forums, blogs and microblogs, Wikis, news sites, picture sharing sites, podcasts, and social bookmarking sites. Enormous amounts of data are archived to meet businesses' various needs. To prepare a data set for the understand stage, various pre-processing steps may be performed, including data modeling, data/record linking of data from different sources, stemming, part of speech tagging, feature extraction, and other syntactic and semantic operations that support analysis. Information about businesses, users, events, user comments and feedback, and other entities are also extracted for later analytical modeling and analysis.

The capture stage must balance the need for finding information from all quarters (inclusivity) with focusing on sources that are most relevant and authoritative (exclusivity) to assist in more refined understanding (stage 2).

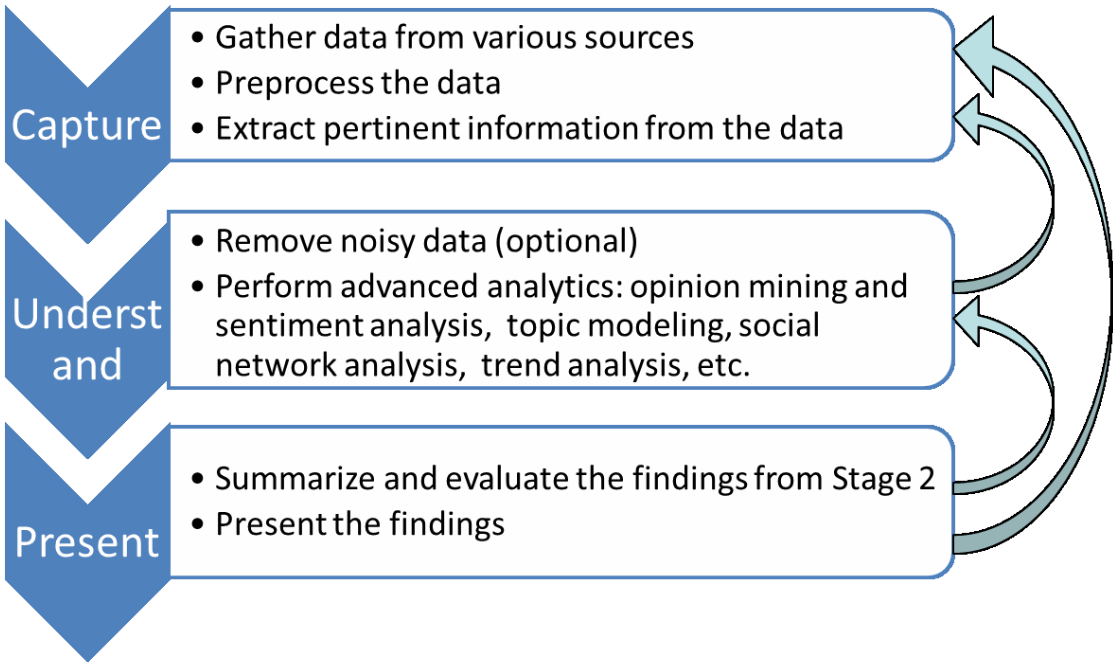

Figure 1: Social Media Analytics Process

Stage 2: Understand

Once a business has collected the conversations related to its products and operations, it must next assess their meaning and generate metrics useful for decision-making. This is the *understand* stage. Since the *capture* stage gathers data from many users and sources, a sizeable portion may be noisy and may need to be removed prior to performing any meaningful analysis. Simple, rule-based text classifiers or more sophisticated classifiers trained on labeled data may be used for this cleaning function. Assessing meaning from the cleaned data can involve various statistical methods and other techniques derived from text and data mining, natural language processing, machine translation, and network analysis [9]. This stage provides information about users' sentiments—how they feel about the company and its products—and their behaviors (including the likelihood of them purchasing in response to an ad campaign, for instance). Many useful metrics and trends about users can be produced in this stage, covering their backgrounds, interests, concerns, and networks of relationships.

Note that the understand stage is the core of the entire social media analytics process. The success of this stage will have significant impact on the information and metrics that are displayed in the *present* stage, and thus the success of future decisions or actions that might be taken by a firm. Depending upon the techniques being used and the information being sought, certain analyses may be pre-processed offline while others are computed on-the-fly using data structures optimized for anticipated, ad hoc uses. Humans may participate directly in the understand stage when visual analytics are used to allow them to see various types and representations of data at once or to create visual "slices" that make patterns more apparent.

Stage 3: Present

The last stage in the social media analytics process is the *present* stage. The results from different analytics will be summarized, evaluated, and shown to users in an easy to understand format. Various visualization techniques may be used to present useful information. One of the most commonly used interface designs is the visual dashboard, which aggregates and displays information from various sources. Sophisticated visual analytics go beyond simply displaying information. By supporting customized views for different users, they help make sense of large volumes of information, including patterns that are more apparent to people than machines. Data analysts and statisticians may add extra support during this stage.

Key Social Media Analytic Techniques

Social media analytics is a growing area that encompasses a variety of modeling and analytical techniques from different fields. We highlight below those that are most instrumental in understanding, analyzing, and presenting large amounts of social media data. These techniques can support various stages of social media analytics. Sentiment analysis and trend analysis primarily support the *understand* stage. Topic modeling and social network analysis have primarily applications in the *understand* stage but can support the *capture* and *present* stages as well. Visual analytics spans the *understand* and the *present* stages.

Opinion mining (or sentiment analysis) is the core technique behind many social media monitoring systems and trend analysis applications.[2] It leverage computational linguistics, natural language processing and other methods of text analytics to automatically extract user sentiments or opinions from text sources at any level of granularity (words or phrases up to entire documents). Such subjective information extracted about people, products, services, or other entities support various tasks including predicting stock market movements, determining market trends, analyzing product defects, and managing crises.

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[2] As Pang and Lee [15] explain, the terms *opinion mining* and *sentiment analysis* each have various definitions. We adopt their definition, which uses both terms broadly and interchangeably to cover the subjective, textual evaluation of items or of their features.

Relatively simple methods for sentiment analysis include word (phrase) counts (the more a product is mentioned, the more it is assumed to be liked); “polarity lexicons” (lists of positive and negative terms that can be counted when used, say, in a text message that mentions a product by name) [11]; and semantic methods (which may compute lexical “distances” between a product’s name and each of two opposing terms, such as “poor” and “excellent” to determine sentiments about it [25]. More complicated approaches must distinguish the sentiments about more than one item referenced in the same text item (sentence, paragraph, text message) [10].

All told, both sophisticated and simple methods of sentiment analysis can be effective or flawed (though most research involving texts, tweets, and other short messages has studied simple techniques.) Though sentiment analysis is becoming more common, we must realize that sampling biases in the data can badly skew results—even if we might confuse large data samples for unbiased samples—perhaps especially in situations where satisfied customers remain silent while those with more extreme positions incessantly voice their opinions.

Topic modeling is used to sift through large bodies of captured text to detect dominant themes (topics). The themes uncovered can be used to provide consistent labels to explore the text collection further or to build effective navigational interfaces. Themes revealed by topic modeling can also be used to feed other analytical tasks such as discovering user interests, detecting emerging topics in forums or social media postings, or summarizing parts (or all) of a text collection. Recent advances in topic modeling also allow these algorithms to be used with streaming data from Twitter and other continuous data feeds, making this technique an increasingly important analytic tool.

Topic modeling uses a variety of advanced statistics and machine learning techniques. For instance, a number of models identify "latent" topics by using the co-occurrence frequencies of words within a single communication [14], or between topics and communities of users [27]. Information about the position of words within messages can also be taken into consideration [26]. Please refer to [4] for a recent survey of this area.

Social network analysis is used to analyze a social network graph to understand its underlying structure, connections, and theoretical properties as well as to identify the relative importance of different nodes within the network. A social network graph consists of nodes (users) and associated relationships (depicted by edges). The relationships are typically detected from user actions directly connecting two people (such as accepting another user as a "friend"), though they may be inferred from indirect behaviors creating relationships, such as voting, tagging, or commenting.

Social network analysis is used to model social network dynamics and growth (network density, locations of new node attachments, etc.) that can help monitor business activity. Social network analysis is the primary technique for identifying key influencers in viral marketing campaigns on Twitter or other social media platforms. It is used to detect sub-communities within a larger online community such as a discussion forum, allowing for greater precision in tailoring products and marketing materials. It has strong uses in predictive modeling, such as conducting marketing campaigns aimed at those assumed mostly likely to buy a particular product [5].

Social network analysis uses a variety of techniques pertinent to understanding the mathematical structure of graphs [18]. These range from simpler methods (such as counting the number of edges a node has or computing path lengths) to more sophisticated methods that compute eigenvectors (similar to the way Google's PageRank algorithm does) to determine key nodes in a network. (This can be used, for instance, in determining who a business might look to on the basis of their expertise, reputation, etc.). The analysis of network structure significantly predates the advent of social media, being developed mainly to analyze static mathematical graphs. Today's large and continually changing network structures are demanding new technical approaches, especially when real-time decision support is sought.

Trend analysis is used for identifying and predicting future outcomes and behaviors based on historical data collected over time. Applications of trend analysis include forecasting the growth of customers or sales, predicting the effectiveness of ad campaigns, staying ahead of shifts in consumers' sentiments, forecasting movements in the stock market, etc. Trend analysis is based upon longstanding statistical methods such as time-series analysis or regression analysis [1] and other more recent modeling techniques such as neural networks [12] and support vector machines [20].

Visual analytics is "the science of analytical reasoning facilitated by interactive visual interfaces"[23]. Initially spurred on by U.S. defense needs, visualization works across different application areas to support synthesis, exploration, discovery, and confirmation of insights from data that are typically voluminous and spread among different sources.

Visual analytics involves a range of activities, from data collection to data-supported decision-making. Though many statistical methods underlie visual analytics (such as reducing high-dimensional data to fewer, and very salient, dimensions), humans' abilities to perceive patterns and draw conclusions are key factors as well. Indeed, when there is a torrent of information that must be acted upon quickly, this combination of machine- and human-strengths is critical, both in making a decision and being able to explain and justify it. Visual analytics shares a focus with other visualization techniques on creating economical, intuitive displays, but unlike the classical work of Tufte [24], these displays must support real time decision-making where the stakes can be high.

Visual analytic systems must be able to process data to reveal their hidden structure as well as their detail. Computational methods for data reduction, displaying correlations among disparate data sources, and allowing the user to physically manipulate data displays all underlie visual analytics. From a more user-perceptual perspective, visual analytics can be regarded as a collection of techniques that use graphical interfaces for presenting summarized, heterogeneous information that helps users visually inspect and understand the results of underlying computational processes. One of the commonly used interface designs is a dashboard where different metrics and key performance indicators are portrayed in a way that mimics a car's dashboard design (see Figure 2). Typically, displays allow a user to interactively interrogate the underlying data and perform data transformations using sliders or other types of controls. Both crisis management and detecting breaking events from social media chatter can greatly benefit from visual analytics. The challenge for visual analytics is to remain responsive to, and create better visual representations for, increasingly massive and complex data requiring speedier interpretation and display on an ever-increasing number of devices (from handhelds to full-wall display panels).

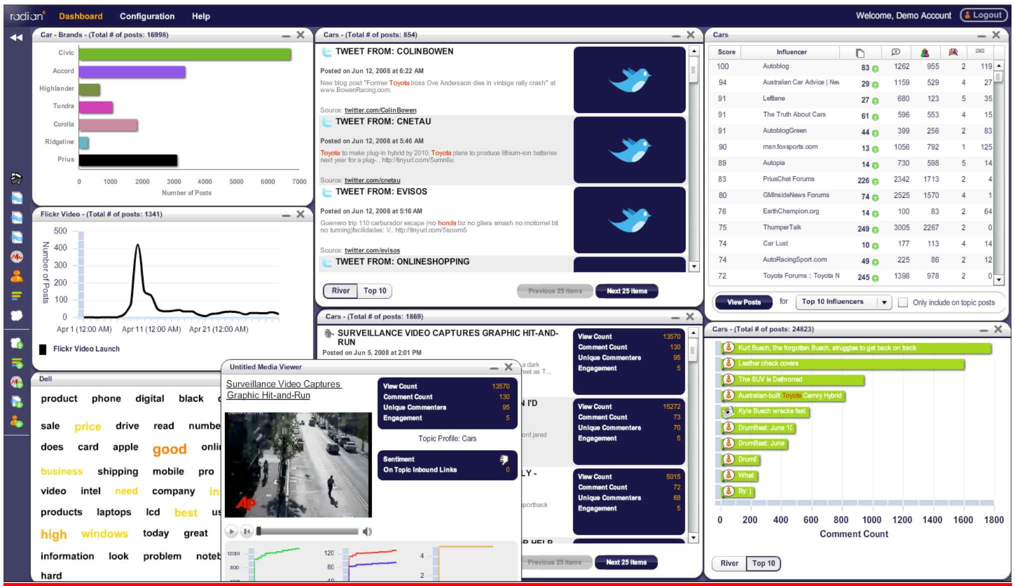

Figure 2: Example of Radian6 Dashboard

The Business Value of Social Media Analytics

As we have suggested in discussing various techniques that support social media analytics, there are a variety of business uses to which they can be put. Here, we consider those uses in more detail. We adopt a life cycle analysis framework.

Social media has changed our conversations about products and services but not the business activities underlying them. A life cycle analysis perspective considers the life of a product (or service) from its design through its disposal, as well as support activities that take place in parallel with these activities. Though different authors describe the product life cycle with different levels of granularity, one that is quite typical suffices for our purposes, having these four stages: design-development; production; utilization; and disposal [2]. Social media is most relevant to the design-development and utilization stages, both of which we emphasize in our discussion. In addition, we comment as well on how social media analytics help firms gather competitive intelligence, i.e., help firms understand more completely their business environment, suppliers, and competitors. Our use of a life cycle framework is consistent with other social media analyses [5].

Product design-development

The first life cycle stage, product design-development, covers the conceptual, preliminary, and detailed design of a product. Various risks threaten success during this stage [3]: Risks involving technology change may arise from misjudging the gaps in technology among different products or from time-to-market pressures. Design risks may arise from a poor selection of product features, from an improper differentiation with other products, a design's lack of modularity, or a reliance on the wrong parts.

Trend analysis and other social media analytic tools can help bring to the fore any changes in tastes, behaviors, and other sentiments that can affect product design and development. These tools can enable features to be added or adjusted, and they can help create sufficient lead time for creating "next generation" products or even products in a completely new category.

Social media analytics can also promote product innovation by capturing and understanding conversations involving either of two groups. On the one hand, a business's most fanatic customers can reveal important insights, as Del Monte found in creating and launching product in just six weeks. On the other hand, conversations with "average" customers can also lead to product improvements. For instance, Dell created its IdeaStorm website to solicit users' ideas about improving its products and services. Dell takes these suggestions into serious consideration, soliciting comments from others as (dis-) confirmation, and, when warranted, making changes to its products.

The software industry has taken the lead in social media-based product testing (thus leading to changes to software) by releasing various versions of its products and soliciting reactions (and, in the case of open source programs, allowing user changes). Other industries, too, are following suit. The most advanced use of social media-based conversations is in the "co-creation" of products, where online users and businesses act as informal partners in generating new product ideas and even entirely new product categories [16].

Product Production

The risks during this life cycle phase involve supply chain responsiveness [3]. Social media analytics can mitigate these risks. By being attuned to changing tastes and behaviors, businesses can anticipate significant changes in demand and adjust accordingly, whether by ramping up or down production. Visual analytics can be useful in pointing out correlations, outliers, geographic patterns, or other trends that support smother functioning.

A business may use social media analytics, too, to learn that another business with which it competes (or perhaps doesn't) is having trouble with a supplier, which can be useful in helping it anticipate and avoid the same problem, even though it is not yet experiencing it. Close monitoring of social media can even help in technical-administrative tasks. For instance, inventory management is based on forecasts and production schedules. Social media may give advance warning when situations become less predictable, including political tensions overseas that could disrupt the flow of metals, minerals, or other vital supplies for manufacturing.

Product Utilization

The most common use of social media analytics is during the product utilization life cycle stage. During this stage, there are three, key social media objectives: brand awareness, brand engagement, and word of mouth [13]. Brand awareness introduces customers to a brand (or product) or increases their familiarity. Brand engagement increases users' connection with a brand. Word of mouth encourages users' attempts to positively influence other users' behavior.

Various metrics have been proposed for assessing social media effectiveness during this stage [13]. For microblogging platforms including Twitter, simple metrics include: number of tweets and followers (for brand awareness); number of followers and replies (for brand engagement); and number of retweets (for word-of-mouth). Although these metrics can provide important information, they are no substitute for more powerful techniques that are increasing in importance in the era of social media.

For instance, influencer profiling uses social media to develop a deep understanding of different users' backgrounds, tastes, and buying behavior to create better customer segmentation. Segmentation assists a business in more effectively reaching various groups, by using these differences to create different strategies for increasing brand awareness and engagement for each of them. Influencer profiling also assists in identifying social-community leaders or experts, both of whose opinions are quite valuable in product development and even consumer-supported customer service. A variety of techniques support influencer profiling, including social network analysis, topic modeling, and visual analytics.

Brand engagement suggests that one feels a personal connection to a brand. Psychometric constructs suggesting brand engagement include the terms “special bond,” “identify with,” and “part of myself” [19]. To attempt to create this level of relationship, companies create a variety of activities. Simple examples are “liking” or “commenting” on a product website. Other activities aim to generate a deeper sense of connection, often by enticing playful user actions. For instance, the car manufacturer Audi was the first to use a then still-novel hashtag in its 2011 Super Bowl ad, showing partying, good looking vampires, and concluding its commercial with the #SoLongVampires. This memorable hashtag could be tweeted during the most-watched sporting event of the season. More important, social media tools were then used to follow users who tweeted with this hashtag to initiate a real-time dialogue that was one step, among many, of cultivating relationships with potential new customers. To the benefit of Audi and its brand, by the end of the game the hashtag had been become a trending topic on Twitter.

More broadly, social media analytics can allow a business to judge online reaction to any ad campaign. The metrics produced can help link the campaign to subsequent sales and thus the success of the campaign. Users’ reactions may also help in altering the campaign in accordance with users’ likes and dislikes. Sentiment analysis, trend analysis, and network analysis all provide useful support.

Word of mouth extends consumers engagement from interactions with products to other consumers. Businesses hope these interactions (through retweets, reblogs, social tagging, etc.) are positive; they are not always.

Customers' online complaints about products and services are common, with, for instance, nearly two-thirds of all customers already using social media for this purpose. More than half of online users expect a response to a complaint within the same day but fewer than one-third receive one. A majority of top 50 brands never respond even to customer comments on their own websites, which obviously hurt their brand image and reputations [17]. Viral spreading of user complaints through social media can significantly affect firms.

Tools like real-time sentiment analysis and topic modeling allow a business to know how its customers feel about its products and services and to respond quickly before customer complaints become an online, negative torrent. Unofficial social media data were harnessed to confirm the characteristics of the cholera outbreak in Haiti following the 2010 earthquake two weeks before the government and international aid agencies were able to do so using more formal means [8]. Similarly, social media data provide early warnings that, left unattended, can create impressions of a business that are hard to overcome.

A study of twenty brand marketers showed that the top 1% of a website's audience shares up to one-fifth of all links to the site and influences up to one-third of the actions that other users take [22]. Social network analysis can be used to determine who these key users are so that they remain satisfied, engaged, and ideally help a business market its products on its own website and via word of mouth over these users' social networks.

Product Disposal

Nearing the end of a product's life, a consumer may face decisions about how to dispose of it, and what to replace it with. For a number of consumers, being able to ecologically responsibly dispose a product (possibly a computer) may influence their overall impression of a company and its products. Thus, making this convenient and ensuring that consumers are aware that it is convenient, is important. Social media analytics can track and companies themselves can engage in conversations covering disposal. Savvy companies that track these social media conversations can, of course, also infer that disposal may be accompanied by a purchase of a replacement item and use that in their marketing.

Competitive Intelligence

So far, our discussions of business values of social media analytics using the life cycle framework focus primarily on the firms' products/services and their customers. Social media analytics also provide a business with value by helping it understand its environment, suppliers, competitors, and overall business trends—in addition to its own customers and products – to stay competitive. We call this value as *competitive intelligence*. We have discussed how social media analytics can reduce a firm's production risks by monitoring conversations about other firms in its ecosystem. Unlike gathering business intelligence from other sources, obtaining information from social media about suppliers or competitors—in all that they do—is almost as easy for a business to do as monitoring its own affairs.

There is one final way in which social media analytics can play a key role: identifying and responding to crises. Ironically, businesses often cause these crises through their own efforts at disseminating messages over social media.

Large organizations, including Burger King, the American Red Cross, and Chapstick were implicated in social media messages that were ill-received (though, in the case of the Red Cross, disseminated accidentally). The first two firms quickly acknowledged their mistakes and took decisive actions. (The Red Cross very deftly defused a potential crisis, first by responding with humor, and then, after identifying the uncommon hashtag in the inadvertent message sent out from its account, using it to follow up to generate a successful blood donation campaign.) Unlike Burger King and the Red Cross, Chapstick at first failed to respond to consumers' complaints at all and then removed them from its site without responding. These actions exacerbated the bad publicity it generated from its online presence.

Challenges and Conclusions

The social media landscape is vast and changing. Even as some social media websites explode into use, quickly becoming every day tools (Facebook, launched in 2004; Twitter in 2006), new platforms are joining them constantly (consider Pinterest, launched in Summer 2011,which already has approximately 50 million users). All told, there are a dozen sites with at least one hundred thousand registered users, and many more unique visitors—including sites most of us have never heard of, like Ozone and Sina Weibo.

Even as businesses begin to realize the peril in ignoring social media content and, conversely, the opportunity it presents, their questions reveal how much remains unknown. A survey of 3,800 marketers indicated their top concerns [21]:

- How to track social media return on investment
- How to identify and engage with the most influential social media users
- What tactics to use to create an effective social media strategy

Social media analytical tools are designed to address questions like these. At the same time, social media are transforming the very nature of business. Current patterns suggest that social media could produce an additional $940 billion in annual consumption, especially in electronics, hardware, software, and mobile technologies [7]. As we have suggested, social media are now supporting the "co-creation" of products, with consumers working online with companies' product designers [16].

As these new commercial frontiers open, technical challenges loom. The extraordinary volume of "big data" will challenge social media analytics [6]. Language issues add further complications as businesses begin to monitor and analyze social media conversations around the world. These challenges may swell as social media analytics begin to incorporate user-based location data facilitated by mobile technology and pressures rise to process and respond to social messages in real-time.

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