

FRENDS & CONTROVERSIES

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Business and Market Intelligence 2.0

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usiness Intelligence (BI), a term coined in 1989, has gained much traction in the IT practitioner community and academia over the past two decades. According to Wikipedia, BI refers to the "skills, technologies, applications, and practices used to support decision making" (http:// en.wikipedia.org/wiki/Business_intelligence). On the basis of a survey of 1,400 CEOs, the Gartner Group projected BI revenue to reach \$3 billion in 2009.1 Through BI initiatives, businesses are gaining insights from the growing volumes of transaction, product, inventory, customer, competitor, and industry data generated by enterprise-wide applications such as enterprise resource planning (ERP), customer relationship management (CRM), supply-chain management (SCM), knowledge management, collaborative computing, Web analytics, and so on. The same Gartner survey also showed that BI surpassed security as the top business IT priority in 2006.1

BI has been used as an umbrella term to describe concepts and methods for improving business decision making by using fact-based support systems. BI also includes the underlying architectures, tools, databases, applications, and methodologies. BI's major objectives are to enable interactive and easy access to diverse data, enable manipulation and transformation of these data, and give business managers and analysts the ability to conduct appropriate analyses and then act.² BI is now widely adopted in the world of IT practice and has also become popular in information systems curricula.³ Successful BI initiatives have been reported for major industries—from healthcare and airlines to major IT and telecommunications firms.²

As a data-centered approach, BI relies heavily on various advanced data collection, extraction, and analysis technologies.^{2,3} Data warehousing is often considered the foundation of BI. Design of data marts and tools for extraction, transformation, and load (ETL) are essential for converting and integrating enterprise-specific data. Organizations often next adopt database query, online analytical processing (OLAP), and advanced reporting tools to explore important data characteristics. Business performance management (BPM) using scorecards and dashboards allow analysis and visualization of various employee performance metrics. In addition to these well-established business analytics functions, organizations can adopt advanced knowledge discovery using data and text mining for association rule mining, database segmentation and clustering, anomaly detection, and predictive modeling in various information systems and human resources, accounting, finance, and marketing applications.

Since about 2004, Web intelligence, Web analytics, Web 2.0, and user-generated content have begun to usher in a new and exciting era of business research, which we could call Business Intelligence 2.0. An immense amount of company, industry, product, and customer information can be gathered from the Web and organized and visualized through various knowledge-mapping, Web portal, and multilingual retrieval techniques.⁴ By analyzing customer clickstream data logs, Web analytics tools such as Google Analytics provide a trail of the user's online activities and reveal the user's browsing and purchasing patterns. Web site design, product placement optimization, customer transaction analysis, and product recommendations can

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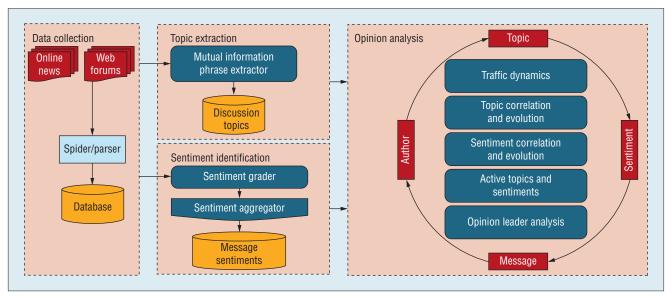


Figure 1. The Market Intelligence 2.0 system architecture. MI2 collects data from online news and Web forums. It extracts topics using the mutual information method, and sentiment using SentiWordNet.⁵ It performs opinion analyses including traffic dynamics, topic and sentiment evolution, active topic and sentiment, and opinion leader analysis.

be easily accomplished through Web analytics.

More recently, the Web 2.0 phenomena have created an abundance of user-generated content from online social media such as forums, online groups, blogs, social-networking sites, social multimedia sites (for photos and videos), and even virtual worlds. In addition to capturing entertainment-related content and sociopolitical sentiments expressed in these media, Web 2.0 applications can efficiently gather a large volume of timely feedback and opinions from a diverse customer population for many different businesses-a practice called crowd-sourcing. Many believe social media analytics presents a unique opportunity for business researchers to treat the market as a "conversation" between businesses and customers instead of the traditional businessto-customer "marketing." Advanced information extraction, topic identification, opinion mining, and timeseries analysis techniques can be applied to traditional business information and to new BI 2.0 content for various accounting, finance, and marketing applications-enterprise risk assessment and management, credit rating and analysis, corporate event analysis, stock and portfolio performance prediction, viral marketing analysis, and so on.

An Example: Market Intelligence 2.0 for Wal-Mart

Traditional marketing research often relies on time-consuming methods involving surveys, interviews, and focus groups to extract opinions and feedback from a small group of target customers. Although the process is systematic, it suffers from slow response and small sampling. The emergence of user-generated Web 2.0 content has begun to offer another opportunity for researchers and practitioners to listen to the voice of the market-as articulated by a vast number of business constituents including customers, employees, investors, and the media.

In recent research, we developed a Market Intelligence 2.0 (MI2) analysis framework that applies automatic topic and sentiment extraction methods to online discussions to assess the opinions of business constituents toward a given company. Figure 1 shows the MI2 system architecture.

We conducted a case study on Wal-Mart by analyzing the message traffic, topics, and sentiments of the online Web 2.0 discussions from Wal-Mart customers, employees, investors, and the media. We chose multiple Web forums that represent different types of online opinions:

- *investor opinions*, from the Yahoo Finance Wal-Mart message board (Yahoo, 1999–2008, 441,954 messages, 25,500 users);
- *employee opinions*, from the Walmart-blows.com employee department board (EMP, 2003–2008, 102,240 messages, 2,930 users);
- *customer opinions*, from the Walmart-blows.com Wal-Mart sucks board (WSB, 2003–2008, 19,624 messages, 1,855 users) and from the Wakeupwalmart.com general Wal-Mart discussion forum (GDB, 2005–2008, 23,940 messages, 967 users); and
- media opinions, from Wall Street Journal news containing information on Wal-Mart (WSJ, 1999– 2007, 4,081 articles, 657 authors).

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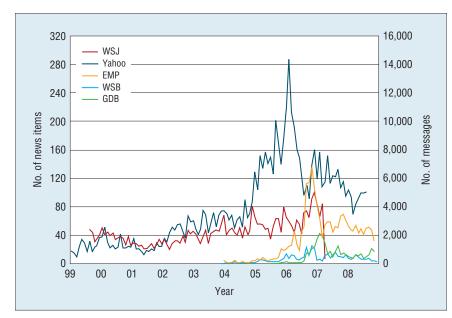


Figure 2. Message traffic for all five data sources, 1999–2008: *Wall Street Journal* (WSJ), Yahoo Finance Wal-Mart message board (Yahoo), Walmart-blows.com employee department board (EMP), Walmart-blows.com Wal-Mart sucks board (WSB), and Wakeupwalmart.com general discussion board (GDB).

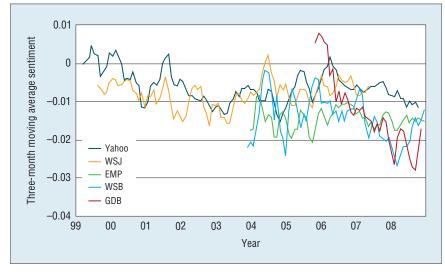


Figure 3. Three-month moving average of sentiment scores for all five data sources, 1999–2008: WSJ, Yahoo, EMP, WSB, and GDB.

We used MI2 to extract and analyze all data. Clearly such a collection presents a unique resource for deriving market intelligence about Wal-Mart. Our initial analysis revealed significant trends in opinion.

Figure 2 shows message traffic for all five data sources. Despite variations in message posting, message traffic rose steadily from 1999 to peak around 2006–2007. Subsequent message traffic decreased significantly. The three-month moving average of sentiment scores for all five data sources (Figure 3) also reveals a decreasing trend in sentiment for almost all Web content. This is clearly something to which Wal-Mart needs to pay special attention.

Our topic analysis revealed that healthcare, the minimum wage, customer service, unfair labor practices, jobs going overseas, and union membership are some of the major topics that have drawn negative sentiment towards Wal-Mart since 2006, as indicated by contributions of the top five active authors in the Yahoo forum (Table 1).

In this Issue and the Next

In this issue of *IEEE Intelligent Systems* and the next, we include five short articles on Business and Market Intelligence 2.0 from distinguished experts in marketing science, finance, accounting, and computer science. Each article presents a unique, innovative research framework, computational methods, and selected results and examples.

In our first article in this issue, "The Phase Transition of Markets and Organizations: The New Intelligence and Entrepreneurial Frontier," Robert Lusch, Yong Liu, and Yubo Chen characterize phase transition in markets and organizations as a move from individuals and resources being separate to being together. It is a move toward a collaborative, service-dominant network. They believe that computational linguistics, sentiment analysis, and network analysis will become increasingly important for extracting market and business intelligence.

In the second article, "User-Generated Content on Social Media: Predicting New Product Market Success from Online Word of Mouth," Yong Liu, Yubo Chen, Robert Lusch, Hsinchun Chen, David Zimbra, and Shuo Zeng, explore the predictive validity of various text and sentiment measures of online word of mouth (WOM) for the market success of new products. We demonstrate the

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Table 1. Top five Yahoo Forum active authors and their contributions.

evolvement patterns of five text and sentiment WOM measures and how they correlate with several key new product metrics.

In the third article, "On Data-Driven Analysis of User-Generated Content," Claudia Perlich, Maytal Saar-Tsechansky, Wojciech Gryc, Mary Helander, Rick Lawrence, Yan Liu, Chandan Reddy, and Saharon Rosset discuss data-driven approaches, including content and network analysis that can be used to derive insights and characterize user-generated content from companies and other organizations. They demonstrate these approaches on the data from IBM's recent "Innovation Jam," which took place in 2007.

In next issue's Trends & Controversies department, look forward to two more articles on Business and Market Intelligence 2.0: "The Finance Web: Internet Information and Markets," by Sanjiv Das; and "Financial Text Mining: Supporting Decision Making Using Web 2.0 Content," by Hsin-Min Lu, Hsinchun Chen, Tsai-Jyh Chen, Mao-Wei Hung, and Shu-Hsing Li.

Acknowledgments

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No of Average Author **Major topics** messages sentiment shep21998 22,557 0.0086 Higher prices, minimum wage, highest unemployment rate briantimlick -0.0183 11.568 Union, jobs moving overseas, unfair labor practices, healthcare costs, competitive wage rates, working conditions, human rights -0.0024 10,012 Healthcare challenges facing, unfair a_ca_gem labor practice charge, employee rights, average hourly wage snerdly76 8,327 -0.0061Higher minimum wage, labor law violation, morally bankrupt company, stock price, earning growth, hiring illegal jimg01523 7,730 -0.0191 Good long-term investments, billion share outstanding, gaining market share, stock price

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The Phase Transition of Markets and **Organizations: The New Intelligence and Entrepreneurial Frontier**

Robert F. Lusch, Yong Liu, and Yubo Chen, University of Arizona

When Adam Smith wrote the Wealth of Nations in 1776, he concluded that individuals, firms, and nations

obtain comparative advantage by specialization.1 Markets worked as the invisible hand to efficiently allocate resources between specialized parties. During the Industrial Revolution, manufacturing organizations helped the nation become wealthy by creating mechanisms for the internal allocation and integration of resources to produce largely tangible output. Today, both markets and organizations are undergoing a phase transition.

The Phase Transition of **Markets and Organizations**

The long history of natural and social systems has seldom been static or linear. Dynamism and nonlinearity occur when an institution converges with emergent societal institutions and technology that bring about phase transitions. Through the past two decades, markets and bureaucratic organizations have been undergoing a phase transition, due primarily to IT innovations and the emergence and proliferation of the Internet and ubiquitous computing.

For much of human evolution, people have not been well connected; they have been separated by large spatial, informational, and temporal gaps. Innovations in land, air, and sea transportation in the 19th century and the

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Table 2.	Phase	transition	of	markets.
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Characteristic	Traditional markets	Phase transition
Primary actors	Firms	Firms, customers, and stakeholders
Locus of control	Firm and market	Network or ecosystem
Primary activities	Firms produce value; customers consume value.	Firms, customers, and stakeholders cocreate value.
Primary coordination mechanism	Price and output, demand and supply	Dialogue and interpretation
Locus of value	Exchange	Use and context
Role of markets	Resource allocation and value exchange	Resource integration for value cocreation

Table 3. Phas	e transition of	f organizations.
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Characteristic	Traditional organizations	Phase transition
Primary metaphor	Bureaucratic organization	Learning organization
Primary orientation	Production and market	Service engagement platform
Exploration/R&D	Internal R&D laboratory	Innovation platform
Going to market	Marketing channel	Exchange platform

first half of the 20th century made it easier for individuals and companies to move themselves around the world. This allowed actors in the marketplace to more easily integrate their ideas and knowledge, and this stimulated innovation. The second-order effect began when the microprocessor and computer networking emerged in the later part of the 20th century. A third-order effect is occurring today as the worldwide use of Internet technologies continues to reduce the temporal gap and the digitization of many resources is reducing the spatial gap.

It is this third-order effect that has triggered a phase transition in the structure of both markets and organizations. The character of the market, what roles the market provides in creating value and the wealth of nations, and how firms should organize to interface with markets, are all being rewritten.

Transitioning from Division to Unification

If we were to sum up the market and organizational phase transition in a single phrase, we would characterize it as a move from individuals and resources being *separate* to being *together*. It is a move toward a collaborative,² service-dominant³ network. Tables 2 and 3 summarize the phase transition in markets and organizations.

No longer can a business operate efficiently and effectively by treating customers, suppliers, and other stakeholders as exogenous or separate from the business itself. No longer can these actors be treated as objects to do something to instead of actors to collaborate *with* for a common purpose. In the past, the organization functioned as a machine that acquired resource inputs to produce products by administratively controlling employees for maximal efficiency, and then distributing these products through intermediaries to other businesses or households; this era is rapidly disappearing. As the organization develops close collaborative relationships with suppliers, customers, and other stakeholders, it is becoming part of an ecosystem whose boundaries extend

beyond the organization itself. As Stephen Vargo and Robert Lusch have argued, this transition is resulting in markets and organizations in which producers, customers, and other stakeholders such as suppliers and employees cocreate value.³ In this world, it is virtually impossible for firms to maximize payoffs in the traditional manner, because of the complexity and dynamics of the ecosystem. However, firms that are more entrepreneurial can use their resources to create effects that expand their resource base within the ecosystem.⁴ Thus, firms can strive to constantly do better via effectuation processes, but they will not be able to maximize.

The Market

The primary means of coordination in markets is becoming dialogue and interpretation. Markets are no longer merely places where buyers and sellers come to exchange offerings and create value in exchange. In the traditional market, price and the firm's output (value in exchange) were the primary coordinating mechanism to allocate resources. Today, economic exchange is embedded within a larger social network, as virtually all actors can connect to each other via advanced telecommunications and the Internet. For this reason, markets are now better characterized as conversations between actors embedded in a network, and these networks are part of a larger societal network.

Markets are increasingly embedded in networks of conversations, which allow different actors to adjust their thoughts and actions as they seek to acquire and integrate market and nonmarket resources to cocreate value. These conversations increasingly have no beginning or end. They are unrestricted in physical, geographic, and temporal space. They often reflect humans' anticipated, lived, and recalled

experiences. Just as prices were a coordinating mechanism in traditional markets, today dialogue and interpretation have become the primary coordinating mechanism in the marketplace. Hence, the marketplace of the future will become proactively collaborative.

The Organization

During this phase transition, the bureaucratic organization is being replaced by a learning organization that is service (not production) oriented. A service-oriented enterprise continuously adapts to stakeholders—such as customers, employees, and suppliers to offer more compelling value propositions. It can sense, anticipate, and respond to these stakeholders. The manager does not rule from the office or desk but as a collaborative partner with others. He or she gains power by helping others realize their potential.

The new organizational mandate is to provide the adaptive and flexible structures that let customers, employees, and suppliers interface with the firm to cocreate value. These structures are becoming known as *platforms*. As we will see shortly, they take a variety of forms but are all supported by computing technology that allows both internal and external customers, suppliers, and stakeholders to provide service to one another.⁵

Platforms should be relatively easy for the customer (and suppliers) to interface with and easy to replicate and scale as the firm expands in size. Consequently, platforms often incorporate a modular architecture that allows the enterprise, suppliers, and customers to be loosely coupled to a business ecosystem. Also critical to well-functioning platforms is a shared language and communication system. Interfacing with a platform is usually voluntary, so platforms must offer a competitively compelling value proposition. Finally, these platforms must be able to sense, anticipate, and respond to customers and suppliers.

In addition to the basic software system that enables enterprise platforms (such as SAP's enterprise resource planning software), three generic platform types are emerging in organizations: service engagement platforms, innovation platforms, and exchange platforms.

Service-Engagement Platforms

A service engagement platform allows a firm's customers and other stakeholders to draw upon the organization as a service support system. In household or final consumer markets, the focus is on the human and lived experience that unfolds over time in relation not to the products made and sold in the market, per se, but to particular roles and goals. Virtually all individual actors perform a multitude of roles: parent, worker, consumer, student, and so on. Each actor also has a set of goals such as a health, wealth, and love. In all of these roles and goals, the actor is seeking meaningful experiences. As Table 3 indicates, the service engagement platform and its service orientation is replacing a production and market orientation as the primary organizational orientation.

Innovation Platforms

The human species is constantly striking a balance between exploiting its current competences and niches and exploring for new competences and niches. As humans aggregated into organizations, innovation was internalized and formalized into research and development labs. Recently, however, more organizations are opening their innovation by developing innovation platforms, which encourage collaboration with customers, suppliers, and other stakeholders to accelerate successful innovation.^{2,3}

Exchange Platforms

Commercial society evolved by forming a variety of intermediary institutions to facilitate exchange among actors. These intermediaries emerged brokers, distributors, jobbers, as wholesalers, and retailers. The development of a common medium of exchange (financial currency) was also an important societal innovation. In the current phase transition, Web 2.0 has allowed organizations to create new institutions for exchange; it now sometimes takes place not directly through financial currency but instead through direct trading and resource sharing, using social currency. Exchange platforms are rapidly evolving, and in the future confederations could serve individuals or households by organizing exchange for all of the resources they need or wish to sell.

Market and Business Intelligence

A central challenge given the phase transition in markets and organizations is to make sure that market and business intelligence reflect these new realities. We believe computational linguistics, sentiment analysis, and network analysis will become increasingly important, and we suggest some preliminary thoughts on these topics.

First, firms should supplement traditional measures of market share that are based on value in exchange (price and dollar sales) with metrics such as the following:

- What share of conversation within some relevant context is about an organization versus its competitors? Related measures might include relative sentiments (positive or negative) for the organization versus others.
- What is the quality of conversation? A lot of chatter is noise, so dialogue quality must be measured.

- What are the discordant conversations about a company, theme, or issue?
- Can we track the emergence of new conversations, their convergence with other conversations, and their proliferation and decline?
- How do conversations influence customers, employees, and suppliers?
- What is the meaning that actors and communities cocreate for a brand?

Second, moving beyond value in exchange to value as cocreated and contextualized, firms can develop metrics such as the following:

- When actors use an organization's product(s), what other resources are integrated with it? How can we model this resource network?
- When actors use an organization's product(s), what goals are they trying to reach?
- What is the level of value cocreation that occurs outside of markets (as in home production or social exchange)?
- What are the cocreation benefits to the firm? What resources or expertise does the firm need to engage in successful cocreation activities with customers, suppliers, employees, and other stakeholders?

Third, moving beyond organizations, the three emerging platforms will require intelligence on the following topics to successfully operate:

- experiences (positive and negative) that people have in interfacing with an organization's engagement platform;
- innovation capital created by open innovation platforms; and
- financial and nonfinancial metrics of the success of exchange platforms.

Market and business intelligence will be gathered on a real-time, ondemand basis. Furthermore, as intelligence providers better learn the needs of the service beneficiary, they will not just sense and respond to needs, they will also anticipate potential needs. A key benefit of the World Wide Web is that it is instantly global and local; business intelligence must be defined around this reality. Consequently, intelligence services should be provided on a macro basis for entire organizations or divisions, but also down to the most micro level to let all individuals better serve others.

Without an understanding of how markets and organizations developed during the Industrial Revolution, it is difficult to understand the phase transition that markets and organizations are undergoing. Organizations are quickly becoming relatively flat and continuously learning to cocreate value with customers, suppliers, and stakeholders using service engagement, innovation, and exchange platforms. Markets themselves are increasingly coordinated by conversation, interpretation, and meaning-making. We are on the verge of great value being created through collaboration among ecosystem participants. Enterprises that become more entrepreneurial, and recognize that products will increasingly emerge outside the organizations that make product components, will have an advantage in creating wealth.

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User-Generated Content on Social Media: Predicting Market Success with Online Word-of-Mouth

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Enabled by Web 2.0 technologies, online social media in the forms of discussion forums, message boards, and blogs has become a prevalent channel

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of communication for consumers and businesses. Online social media allows consumers to share their product opinions and experience at an unprecedented pace and scale. This usergenerated content, or online *word of mouth* (WOM), has the potential to influence product sales and firm strategy.^{1,2} Consequently, as Web-mining and opinion-mining tools and technology continue to proliferate, it is critical to examine how WOM information can be measured and used to improve managerial decisions.

In this article, we explore the predictive validity of various text and sentiment measures of online WOM for the market success of new products. From the firms' perspective, it is important to effectively predict the sales of new products in the product development process. The earlier such a forecast can be made, the more useful it will be, since marketing strategies can then be adjusted accordingly. We thus examine online WOM that appears at different stages of the new-product lifecycle, such as before production, before introduction, and after introduction. New-product development is a highly risky process, and it is useful to examine different aspects of its success. In addition to examining product sales directly, we also study product evaluation by third-party professionals and how the product would receive marketing support from the firm, both of which could influence sales.³

The context of our study is the Hollywood movie industry. The forecast of movie sales is highly challenging and has started to incorporate online WOM.² We collected online WOM information from the message board of Yahoo Movies for a total of 257 movies released from 2005 to 2006. We used SentiWordNet and OpinionFinder, two lexical packages of computational linguistics, to construct the sentiment measures for the WOM data.^{4,5} We will first examine the evolution patterns of online WOM over time, followed by a correlation analysis of how various sentiment measures relate to the metrics of new product success.

New Product Lifecycle and Metrics for Success

Consistent with the developmentintroduction-sales process of many new products, the new-product lifecycle for movies can be broadly divided into the following periods:

- 1. preproduction,
- 2. from production to movie release,
- 3. from release to the first week of sales,
- 4. from the first to the fourth week of sales, and
- 5. the sales period after the fourth week.

Among these distinctive periods, the first week after release is critical for movies because it captures a large share of the total box office sales and also influences the distributional support in subsequent weeks. We also use the fourth week after release as a critical time, because movie exhibition contracts usually require a minimum number of weeks; four is a common minimum. We collected and measured online WOM for each of these periods: in different periods of the product lifecycle, the product information available to consumers varies, and thus online WOM can carry different informational value and predictive power.

We examined five different metrics of new product success for the movie sample: two final sales measures (opening-week box office and total box office sales), and three intermediate measures that can affect sales (professional evaluation, distribution intensity, and distribution longevity). In many markets, third-party professionals provide valuable and credible information about new-product quality.^{1,3} Their reviews and evaluations can influence consumer opinions and thus influence product sales. For the movie sample, we collected third-party professional evaluations (that is, critical reviews) of each movie from Metacritic. com, which assigns a numerical score between 0 and 100 for each review.

Firm marketing strategies can also significantly influence final product sales. We studied two important movie marketing strategies—the distribution intensity of a movie in the opening week (opening strength), and the total number of weeks that a movie is shown in theaters (longevity).

Text and Sentiment Measures of Online WOM

Other studies of online WOM, and research on traditional WOM, have identified volume (the amount of communication, usually measured by the number of messages) and valence (WOM being positive or negative) as two important measures of WOM activity. Recent development in opinion mining and computational linguistics has made it possible to employ training and identification techniques to construct more fine-tuned measures. Two important contributions to sentiment analysis are the development of OpinionFinder and SentiWordNet, which assign scores such as positivity, negativity, and objectivity to the texts.^{4,5}

We examined five text and sentiment measures of online WOM: number of messages, valence, subjectivity, number of sentences, and number of valence words. Valence is the degree of positivity and negativity, with a score of zero indicating neutrality, more positive values indicating more positive opinions, and more negative values indicating more negative opinions. Subjectivity is the degree to

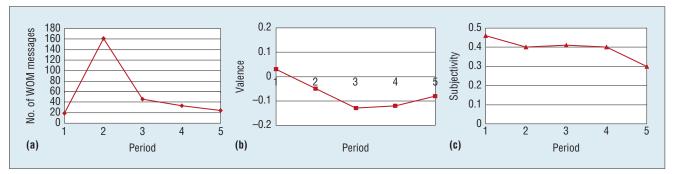


Figure 4. Evolution of online word of mouth (WOM) over product lifecycle: (a) number of WOM messages; (b) valence, the positivity or negativity of the WOM; and (c) subjectivity of the WOM. Period 1: preproduction; Period 2: from production to movie release; Period 3: from release to the first week of sales; Period 4: from the first to the fourth week of sales; Period 5: sales period after the fourth week.

which a message is subjective or objective, with a lower bound of 0 indicating highly objective opinions and a higher bound of 1 indicating highly subjective opinions.

Evolution of Online WOM Communications over Product Lifecycle

Figure 4 illustrates the evolution of three WOM measures (number of messages, valence, and subjectivity) across the five time periods of movie lifecycle. The patterns show that WOM communication starts early in the preproduction period, becomes highly active before movie release, and gradually diminishes as the movie is shown for more weeks in theaters. Valence has a clear decreasing trend over time, especially from the prerelease period to the opening week, indicating that WOM becomes more negative after movies are released. The subjectivity measure, as well as the number of sentences and the number of valence words per WOM message (not shown due to space limitations), remain fairly stable over time.

How do the measures of WOM correlate with each other in each time period and over time? First, there is a negative correlation between valence and subjectivity, especially for the time periods after movie release (p < 0.05). This suggests that more negative WOM tends to be conveyed in more subjective statements. Second,

messages that have a greater number of sentences tend to be more subjective (p < 0.01). Third, there is a negative correlation between valence and the number of valence words used (p < 0.01), indicating that consumers tend to use more evaluative expressions to express negative opinions.

Across different time periods, the numbers of messages during preproduction, from production to release, and in the opening week are significantly correlated with each other (p < 0.01). If the number of messages is a useful indicator of future product sales, this pattern suggests that sales forecast can be made as early as the preproduction period. Valence during preproduction is positively correlated with that prior to release. However, valence during preproduction does not correlate with the valence during the opening week and those in later periods. The degrees of subjectivity have patterns over time similar to those for valence.

Correlation between WOM and New-Product Performance Metrics

Table 4 presents the correlation between the WOM measures and the five new-product metrics. In terms of professional evaluations, the number of messages and the number of sentences per message are consistently the most useful predictors, starting with Period 2 (from production to release). A movie that receives more active WOM communication tends to receive higher evaluations from movie critics, suggesting the number of messages could work as a signal for product quality. Interestingly, if a movie attracts more detailed WOM messages (a larger number of sentences on average per message), it also tends to gain higher evaluation from professional critics. One explanation is that such movies might have more sophisticated story line and higher artistic value, two key attributes of product quality that professional critics pay attention to.

The number of WOM messages prior to movie release, but not the number of WOM messages before movie production, is a useful predictor of the movie's opening strength. The movie's longevity is significantly correlated with the number of WOM messages prior to movie release and before movie production.

To predict movie box office sales, both for the opening week and the US gross, the number of WOM messages is consistently the most significant variable. The number of WOM messages during the preproduction period is highly correlated with both box office measures (p < 0.01).

The valence of WOM appears not to be correlated with any newproduct performance metrics. This is somewhat surprising and indicates that the degree of public attention as captured by the number of WOM

	New Product Success Metrics					
Period	Sentiment measures	Professional evaluation	Opening strength	Longevity	Opening week sales	Total sales
1. Preproduction	Number of messages	0.199	0.112	0.373**	0.530***	0.499***
	Valence	0.139	-0.279*	-0.173	-0.090	-0.085
	Subjectivity	0.378**	0.030	0.171	0.164	0.195
	Number of sentences	0.106	0.029	0.293*	0.027	0.127
	Number of valence words	0.274	0.064	0.262	0.071	0.166
2. Production to	Number of messages	0.249***	0.231***	0.200**	0.676***	0.562***
release	Valence	0.024	-0.047	0.054	-0.046	-0.031
	Subjectivity	0.004	-0.080	-0.042	-0.001	-0.008
	Number of sentences	0.225***	-0.170**	0.049	0.005	0.049
	Number of valence words	0.121	-0.131	0.021	-0.028	0.011
3. Release to first	Number of messages	0.184**	_	0.147*	0.450***	0.391***
week of release	Valence	0.055	_	0.123	0.079	0.065
	Subjectivity	-0.012	_	-0.146*	-0.134*	-0.107
	Number of sentences	0.138*	_	0.012	-0.008	-0.003
	Number of valence words	0.047	_	-0.045	-0.051	-0.040
4. First week to	Number of messages	0.191**	_	0.119	—	0.224***
fourth week of release	Valence	-0.100	_	0.053	—	-0.018
	Subjectivity	0.126	_	0.001	—	0.109
	Number of sentences	0.223***	_	-0.037	—	0.038
	Number of valence words	0.248***	_	-0.062	_	0.024
5. Fourth week	Number of messages	0.146**	_	0.131**	_	0.477***
and later –	Valence	-0.039	_	0.091	_	-0.079
	Subjectivity	0.094	_	0.152**	_	0.225
	Number of sentences	0.228***	_	0.081	_	0.098
	Number of valence words	0.163***	_	0.112	-	0.112

Table 4. Correlations between measures of online word of mouth and new-product success metrics.

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* *p* < 0.10

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** *p* < 0.05 . *** p < 0.01

messages is a more useful predictor for new product performances than the aggregated valence measure. This finding was also consistent with an earlier study on the impact of WOM on movie sales, which provides behavioral rationales for it.²

Overall, the number of WOM messages is the most useful predictor of the five new-product metrics. For the purpose of predicting box office sales, the number of WOM messages as early as prior to movie production

can be used. In addition, to predict how the movies will be received by professional critics, the average number of sentences in WOM messages is another good signal besides the number of WOM messages.

Advances in Web 2.0 technologies make it possible to harness business intelligence from various online social media. A recent trend in both academic research and business practice has been to employ usergenerated and online WOM data for descriptive and normative purposes. For instance, retail recommender systems have started to incorporate consumer reviews and product ratings to improve recommendation effectiveness. At a more general level, these data are useful complements to the traditional sales and shipment data that have been employed to understand consumers and markets. With the development of more and better

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Web-mining and opinion-mining tools, there will be great opportunities for researchers and managers to derive valuable managerial implications embedded in social media.

In this article we demonstrated the evolution patterns of five text and sentiment WOM measures and how they correlate with several key newproduct metrics. Future research should examine the properties of additional text and sentiment measures and explore their value for business applications. Information in different data formats, such as user reviews versus numerical ratings, could have distinctive implications for consumer preference and firm strategies. Similarly, systematic differences might exist among business intelligence gathered from different sources, such as firmsponsored forums and forums operated by independent organizations.

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On Data-Driven Analysis of User-Generated Content

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The prevalence of interactive Web sites such as Facebook, Flickr, My-Space, LinkedIn, and YouTube has drawn millions of users to share their personal views and to converse publicly with other Internet users. Online retailers employ user-generated content to provide product recommendations and product reviews that help facilitate potential consumers' decisions. Our interest is to understanding how data-driven methods can be applied to derive value and insights from other types of user-generated content. Important objectives include

• improving the understanding of user behavior,

- deriving insight from content about topics of interest, and
- improving the usability and economic viability of user-generated platforms and communities.

Increasingly, firms have become interested in better understanding how to make effective use of content from forums and how to capitalize on the joint wisdom of employees. One early effort was IBM's World Jam in 2001, an enterprise-wide brainstorming effort that was followed by similar discussion forums. In this article, we discuss data-driven approaches used to derive insights and to characterize usergenerated content from IBM's Jams.

IBM's Jam

The Jam refers to a social-computing exercise with the object of engaging IBM's global workforce in Webbased, moderated brainstorming.¹ Here we discuss methods for and insights from our analysis of the 2007 Innovation Jam. This Jam proceeded in two phases: The first focused on idea creation, and discussions were seeded with four topics of interest to IBM. Following phase 1, a team of experts evaluated the postings to identify promising ideas, yielding 31 "big ideas." The discussions in phase 2 aimed to transform the big ideas into actual products, solutions, and partnerships that would benefit business or society. Finally, a team of strategists identified 10 finalist ideas to receive funding.

A key corporate objective in running a Jam was to provide an environment that facilitated the generation of creative ideas for IBM to pursue. We discuss data-driven methods that facilitate this objective by characterizing the patterns of interactions as well as the content of Jam contributions. We initially explore the extent to which the Jam environment was

Finalist idea	Phase 1 threads (no.)	Phase 2 threads (no.)	Descriptive stemmed words
Electronic health record system	49	35	patient, doctor, healthcar, diagnosi, hospit, medic, prescript, medicin, treatment, drug, pharmaci, nurs, physician, clinic, blood, prescrib, phr, diagnost, diseas, health
Integrated mass transit information system	59	20	bus, congest, passeng, traffic, railwai, commut, rout, lane, destin, transit, journei, rail, road, vehicl, rider, highwai, gp, driver, transport
Big Green innovations	27	13	Desalin, water, rainwat, river, lawn, irrig, rain, filtrat, purifi, potabl, osmosi, contamin, purif, drink, nanotub, salt, pipe, rainfal, agricultur

Table 5. Examples of topic clusters with the most threads in phase 2 that match finalist ideas.

conducive to produce meaningful, focused discussions. We discuss different metrics to understand whether, in spite of its wide scope, the Jam can facilitate focused discussions. We also discuss opportunities to support and to partially automate evaluation of Jam contributions.

Content Analysis

In evaluating the Jam, we used content analysis to detect the emergence of focused discussions and to help experts effectively search for valuable information.

In this analysis we focused on threads—that is, sequences of postings and responses to these postings. Prior to this analysis we applied several common preprocessing steps (keyword selection, stemming, stoplisting, and so on) to produce a term frequency–inverse document frequency (tf-idf) representation for each thread.

Topic Evolution

The purpose of analyzing topic evolution is to understand

- whether focused discussions emerge during the course of a thread,
- whether the current settings enabled such discussions to emerge early on, and
- whether any changes in the settings are warranted to accelerate the emergence of meaningful, focused discussions.

To determine whether a thread constitutes a focused discussion, we computed content similarity (cosine distance) as a function of time over any 10 consecutive posts. We drew the following post excerpts from a discussion on the topic "digital entertainment." The thread exhibited the highest averaged cosine similarity and was the most focused around 27 hours after the Jam began.

- o "... Going to the movies is a social experience. It is about enjoying the whole experience: large screen, popcorn, people ..."
- "The possible future development in entertainment will be the digital eye glasses with embedded intelligence in form of digital eye-glasses. The advantages for users would be: the screen size and the 'feeling' to be inside the action ..."
- "... Really big screens accompanied by great sound and special lighting effects would really enhance the experience and make it different from renting a movie at home ..."
- "It would be nice if multiple movies could play on the same screen and the audience would wear special glasses so they could see only the movie they paid for."

Contributors initially propose that a distinct and valuable experience for consumers pertains to the large screen size in theaters as well as to the company of other viewers—both of which are difficult to replicate in home theaters. The focused discussion proceeds to develop alternative and economically viable models, which aim to improve on the existing theater experience.

We found that the Jam does enable the emergence of focused discussions.

However, we also found that such discussions rarely emerge early on in the Jam. This may be due to the fact that it takes time for participants to identify discussions of interest to them. Thus, better interface, such as improved search capabilities, might accelerate the emergence of meaningful discussions.

Clustering

A key task for forums that aim to facilitate learning from users is manually reviewing content to identify promising ideas. This is a rather daunting task because similar discussions can take place at different times and within different threads. To efficiently analyze content, it is desirable to automatically identify closely related threads which can be reviewed and evaluated simultaneously.

Clustering analysis can group the posts and characterize each by clusterspecific key terms. We examined several alternative clustering algorithms, which yielded similar results. Henceforth, we discuss the results produced by complete-linkage agglomerate clustering.² Starting from each thread as its own cluster, this algorithm recursively combines the two clusters that have the lowest average Euclidean distance between all pairs of threads in the two clusters. We stopped merging clusters once the algorithm identified 20 clusters.

We found that most clusters (71 percent) included only threads from phase 1 (these ideas were not carried over to phase 2). The remaining clusters reflected discussions in both phase 1 and phase 2 threads. Table 5 shows the two clusters with the largest number

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of threads from phase 2. Interestingly, we find a direct mapping between each cluster and the finalist ideas, selected to be continued in phase 2. For example, the top cluster includes frequent mentions of "patients," "doctors," and "healthcare"; this cluster corresponds to the finalist idea on an "electronic health record system." Our results demonstrate that clustering is effective for grouping related threads, and it offers a valuable tool for efficient evaluation of the content by domain experts.

Network Analysis

We can also use the structure of interactions among users and its dynamics over time to characterize content generation. In what follows, every *node* refers to a contributor, and a directed *edge* from A to B exists if author A posted a response to a post by author B.

To learn about the effectiveness of the Jam in facilitating focused discussions we explored two measures. The first, inspired by the Jaccard coefficient, captures the social network's stability-that is, whether the same contributors are engaged in a discussion over time, and what this time frame typically is. We measured the change over time by comparing networks from adjacent time windows. For two networks with identical nodes N but varying edge sets E_1 and E_2 , we calculated the number of edges present in both networks over the number of total edges:

$$SC(E_1, E_2) = \frac{|E_1 \cap E_2|}{|E_1 \cup E_2|}$$

As a baseline for comparison, we also constructed two random networks by randomly drawing edges from the total social Jam network in phase 1. We found that the similarity ratio is always significantly higher than that of a random network pair. However, the duration of high stability is rather short (around five minutes). Whereas we found that some discussions were adequately focused, our network analysis also suggests that most contributors tended to move quickly between discussions and weren't very likely to engage for long.

The second measure we employed is the network's clustering coefficient. This measure aims to capture the intensity of interactions among contributors and has a nice probabilistic interpretation—it captures the likelihood that the neighbors of a node n have links with each other. It is given by³

$$C(n) = \frac{E(n)}{k(n)[k(n) - 1]}$$

where E(n) is the number of edges among *n*'s neighbors, and k(n) is the number of immediate neighbors that node n has. We found that the average clustering coefficient is approximately 0.052. For comparison, this value is significantly higher than that of a randomly generated network with similar statistics (C = 0.00016), and even than that observed for an email network (C = 0.0344).⁴ However, it is lower than the coefficients observed for networks of professionals who collaborate routinely, such as biomedical researchers, movie actors, and company directors.⁵ Together, these measures suggest that most of the Jam contributors didn't focus continuously on a given topic or were frequent contributors to a given thread.

Companies increasingly draw on their employees and customers for input on improvement and innovation. IBM's Jam was one of the earlier attempts to harvest employee knowledge, and it has led to promising new strategic directions. However, our analyses suggest that focused discussions emerge infrequently and only later in the process. Thus, there is a clear need for improving the Jam process itself.

Our findings have also motivated strategies for improving learning from user-generated content at IBM. Later generations of the Jam have included new design features that address the earlier problems. For example, to help contributors identify threads of interest early on, a recommender-like system directs a participant to a thread that matches her expertise. In addition, a revised incentive structure explicitly rewards participants for their time commitment to encourage participants to engage in focused, extended discussions. Furthermore, on the basis of early Jam threads, potentially valuable contributors are automatically identified as domain experts and receive invitation to participate in later stages of the Jam. This identification is done by matching between the keywords of thread clusters and employee descriptions in the corporate directory.

The success of the Jam was followed by several initiatives to broaden the Jam effort at IBM. In particular, Banter is a system that offers insights about the opinions of customers and users on IBM products or initiatives, as expressed in online blogs. In contrast to the Jam discussed in this article, Banter's content analysis focuses on the sentiments expressed by contributors. Banter also employs topic detection and tracking methodology similar to that discussed in this article, and it computes hubs and authorities within contributor networks to help identify authoritative contributions. SmallBlue is another recent internal social-networking platform that aims to answer questions such as "Who knows what?" "Who knows

whom?" and "Who knows what about whom?" within an organization without requiring explicit human involvement. This effort extends some of the methods discussed here by combining content analysis (of email and personal pages) with network analysis to identify experts in a particular area and their association with other experts.

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