In the past decade and a half we have seen the rise of technologies that have enhanced peer-to-peer interactions: consumers now can check the status of their acquaintances on Facebook, browse through the photos of celebrities on Instagram, check Twitter for the latest updates on breaking news events, text their friends on their smart phones, and read hotel reviews written by strangers on TripAdvisor. One of the more exciting implications of this development from a marketing perspective is that these platforms enable the exchange of product-related information. For example, a Facebook friend may recommend a film that she recently saw, a recipe posted on Pinterest may mention a certain chocolate brand as an ingredient, and a blogger may comment on his experiences with a new digital camera. Moreover, not only is the information being shared to a greater extent on a greater variety of platforms, and among people who may not be as easily connected in the offline setting, but firms can now manage some of the interactions. For example, the firm can promote conversations among its customers and noncustomers by investing in online communities, or perhaps reaching out to certain bloggers.

This chapter summarizes recent research in marketing\(^1\) that relates to the issue of management of social interactions, which we defined in Godes et al. (2005) as an action that is taken by an individual not actively engaged in selling the product or service, and that impacts others’ expected utility for the product or service. In other words, social interaction is a broader concept than the traditional concept of word of mouth (WOM) since it encompasses new electronic types of communication such as email, consumer reviews, and Twitter posts. This chapter is complementary to Chapter 29 by Bloch, which focuses on the targeting of individuals to diffuse information or opinions in a social network, and the pricing at different nodes of the social network in a game with consumption externalities. While there is some overlap between the two chapters,

\(^1\) The chapter also discusses a few related papers in economics, information technology, and finance.
the current work focuses more on social effects, while the chapter by Bloch takes the social effects as given and focuses on the diffusion of information in a network.

The first building block of social interactions is the motivation of the agents involved, which usually means the motivation of the sender. Berger (2014) lists the main motivations behind the generation of word of mouth as: (1) impression management (such as identity-signaling), (2) emotion regulation (for example, generating social support), (3) information acquisition, (4) social bonding, and (5) persuading others. A growing number of papers in the behavioral marketing literature are exploring these motivations and the implications that they have on the type of information that is shared between consumers. For example, if a sender is concerned about self-presentation, she is more likely to talk about products that are perceived as “cool.” The second building block of social interactions is the shape of the social network of the agents, and the position in which they occupy in that network. Many of the papers that we will discuss in this chapter explore the impact of social networks on the diffusion of information.

We use a modified version of the framework developed in Godes et al. (2005) to classify the different roles that the firm can play in managing social interactions: observer, influencer, and participant. While the sender’s motivation certainly has an important bearing on how the firm can optimally manage social interactions, we do not deal directly with the growing behavioral literature on word of mouth, for which Berger (2014) provides excellent coverage. Instead, we focus on the quantitative marketing literature as it applies to these topics.

\section*{30.1 Firm as Observer}

The effectiveness of any management strategy relies in part on the ability to measure. However, there are two primary challenges to measuring social interactions: (1) How can one gather data on what are essentially private exchanges? (2) What aspects of conversations (highly unstructured data) should be measured and are managerially meaningful?

The lack of data availability in the past has implied that researchers traditionally have had two measurement techniques available to them: surveys (Reingen and Kernan 1986) and inference (Bass 1969). The emergence of online communication platforms has implied that conversations that were previously private are now not only public but can be collected by firms as well as by researchers. Below we summarize the various metrics that have been studied in the literature and the extent to which these metrics are relevant to the firm.

\subsection*{30.1.1 Volume}

This is perhaps the most intuitive metric and represents the total amount of conversations about a product within a fixed period of time. There are a number of studies
that have examined the relationship between volume and sales. For example, Godes and Mayzlin (2004) collected posts about new TV shows on public Usenet forums as measure of online conversations and tied them to TV ratings (firm sales in this setting). In that study volume measures the total number of posts across all user groups \((n)\) about a show \((i)\) during the course of the week \((t)\),

\[
POST_{it} = \sum_{n=1}^{N} POST_{it}^n
\]

In other words, here volume measures how many people mentioned the TV show within a week. The study estimates a model of TV ratings as a function of last week’s word-of-mouth measures (including volume), controlling for previous TV ratings and the show fixed effect. Interestingly, Godes and Mayzlin (2004) find that the information provided by the volume metric (how many people mentioned the show) is already contained in the previous sales variable, and hence is not significant once the model includes previous ratings.

Chintagunta et al. (2010) examine the effect of online reviews on box office performance. In that study the volume measure is the number of reviews for a movie in the Yahoo! Movies website, and the dependent variables is the opening-day gross for a title in a local geographic market. They find that the volume of reviews does not have an effect on sales. In contrast, Gopinath et al. (2013) do find a positive relationship between blog volume (the number of blogs that mentioned the movie) and opening-day movie performance, but do not find a significant effect of volume on post-release movie performance. Some of the other studies that do find a significant effect of volume on sales include Dellarocas et al. (2007), Duan, Gu, and Whinston (2008), and Liu (2006).

In summary, the volume metric seems to be a valid measure of online word-of-mouth activity, especially soon after the product release and before sales data becomes available (Gopinath et al. 2013). What is less clear is the extent to which it captures new information about word of mouth above and beyond information contained in past sales (see Godes and Mayzlin 2004).

### 30.1.2 Valence

Valence measures the extent to which a conversation about a product is positive. In the context of online reviews, where a reviewer provides a numerical evaluation score of the experience, obtaining a valence measure is relatively easy, even though the text itself may still provide additional information above and beyond the numerical score. Measuring the valence of all other conversations involves text-processing which can be done either automatically using software or using human raters.

Table 30.1 illustrates the observed valence of conversations across various categories and platforms. Unless otherwise noted, all of the averages for reviews are on the 5-point scale (with “1” being the lowest possible review and “5” being the highest). One observation that we can make is that there is variation in mean valence across categories...
Table 30.1 Valence of Conversations

<table>
<thead>
<tr>
<th>Paper</th>
<th>Context</th>
<th>Valence distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resnick and Zeckhauser</td>
<td>Reviews of sellers and buyers on eBay</td>
<td>99% of buyers and 98% of sellers had positive feedback</td>
</tr>
<tr>
<td>2001</td>
<td></td>
<td></td>
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<tr>
<td>Godes and Mayzlin 2004</td>
<td>Usenet posts on new TV shows</td>
<td>51% of posts were positive, 27% negative, and 22% mixed</td>
</tr>
<tr>
<td>Chevalier and Mayzlin 2006</td>
<td>Book reviews</td>
<td>Average rating on Amazon.com = 4.14</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Average rating on BarnesandNoble.com = 4.45</td>
</tr>
<tr>
<td>Chintagunta et al. 2010</td>
<td>Movie user reviews on Yahoo! Movies website</td>
<td>Average rating of reviews until the movie is released in a new market = 9.9 out of 13</td>
</tr>
<tr>
<td>Moe and Trusov 2011</td>
<td>Product review on the website of national retailer of bath, fragrance, and beauty products</td>
<td>80% of all reviews were five-star</td>
</tr>
<tr>
<td>Godes and Silva 2012</td>
<td>Amazon book reviews</td>
<td>Average rating = 4.09</td>
</tr>
<tr>
<td>Ghose et al. 2012</td>
<td>Reviews of hotels</td>
<td>Average rating on Travelocity.com = 3.87</td>
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<td></td>
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<td>Average rating on TripAdvisor = 3.49</td>
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<tr>
<td>Mayzlin et al. 2014</td>
<td>Hotel reviews</td>
<td>Average TripAdvisor rating = 3.52</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Average Expedia rating = 3.95</td>
</tr>
<tr>
<td>Tadelis and Nosko 2015</td>
<td>Reviews of sellers on eBay</td>
<td>More than 99% of sellers had positive feedback</td>
</tr>
</tbody>
</table>

and platforms. For example, the ratings on BarnesandNoble.com (average of 4.45) are higher than the rating on Amazon.com (average of 4.14), and the ratings for books are higher than the ratings for hotels (average between 3 and 4 stars) and movies (average of 3.8 when translated to 5-point scale). One robust observation has been the fact that reviews on eBay tend to be very high—a working paper by Tadelis and Nosko finds that 99% of sellers had positive feedback.

Perhaps more surprising is the fact that reviews on Amazon.com, where the market is not two-sided, also tend to be quite positive—with an average of about 4.2 out of 5 stars. This could be due to self-selection (people may be able to effectively match themselves to a book based on available information) or could be possibly due to review manipulation. Hotel reviews appear to be more negative on average—with averages below 4 out of 5 stars. Mayzlin et al. (2014) point out that this effect could be due to differences in review manipulation: books on the same subjects may be complements whereas hotels in the same geographic area are substitutes. Hence, there is a more of an incentive for negative review manipulation by close competitors for hotels than for books.
In the context of reviews, several papers have found that valence (the book's average star rating) of reviews affects sales. For example, Chevalier and Mayzlin (2006) examine the effect of Amazon.com and BarnesandNoble.com reviews on book sales. They find that the valence of reviews drives a book's relative sales levels. Interestingly, they also find that the impact of very negative reviews is greater than the impact of very positive reviews. Chintagunta et al. (2010) find that movie reviews valence affects opening-day sales.

As we mentioned above, not all conversations contain a numerical rating. In that case, obtaining measures of valence must involve a more labor-intensive process. Godes and Mayzlin (2004) utilized two (human) coders to categorize Usenet postings as positive, negative, or mixed. A third coder was utilized when there was disagreement between the first two coders. In that paper the authors find that 51% of the relevant conversations are positive, 27% are negative, and 22% are mixed. A similar procedure was used by Gopinath et al. (2013).

Finally, there is a growing body of literature devoted to automated textual analysis. There is a variety of technical challenges associated with automatically mining text data. An excellent primer on the issues is Netzer et al. (2012). The various approaches include supervised machine learning and rule-based or dictionary-based text mining. The difficulty inherent in accurate text-mining can be illustrated by an example of a message board post from Netzer et al. (2012), “That’s strange. I heard many people complaint[sic] about the Honda paint. I owned a 1995 Nissan Altima before and its paint was much better than my neighbor's Accord (1998+ model). I found the Altima interior was quiet [sic] good at that time (not as strange as today's).” Even a human coder might find it challenging to categorize this post's valence about the various brands mentioned.

Despite these challenges, a number of papers have used text mining techniques to extract additional information from online conversations. An early paper by Das and Chen (2007) extracts investor sentiment from online message boards and connects this information to stock performance. More recently, Archak et al. (2011) mine Amazon review data to obtain information on product features. Ghose et al. (2012) aggregate information collected from text analysis and user surveys (conducted on Amazon Turk) to create a hotel ranking system.

### 30.1.3 Variance

In the existing literature, the term variance has stood for two distinct types of measures. The first refers to the amount of disagreement in reviews on the evaluation of product quality. The second refers to the dispersion of conversations across the social network. We examine the two measures in turn.

The variance in the product evaluations has been measured by a few studies. Sun (2012) provides a theoretical foundation for why and how variance in ratings should
affect sales. She presents a model where the consumer infers that the product with a high variance in ratings is in fact a niche product. This implies that a higher variance should only help product sales if the review average is low. The paper also provides some evidence for this effect using Amazon.com and BarnesandNoble.com book reviews. In contrast, Chintagunta et al. (2010) find no effect of review variance on movie sales. Moe and Trusov (2011) find that disagreement among review ratings is associated with a lower subsequent rate of posting of extreme reviews.

Godes and Mayzlin (2004) use entropy to measure the extent of information dispersion across a social network. This metric is motivated by Granovetter (1973) theory of the effect of social network structure on the flow of information. Granovetter characterizes relationships as being either “strong ties” or “weak ties.” If we assume that communities or groups are characterized by relatively strong ties among their members, one implication of this model is that the only connections between communities are those made along weak ties. This has the important implication that information moves quickly within communities but slowly across them, and that the information that traverses a weak, as opposed to a strong, tie has the opportunity to reach more people.

Godes and Mayzlin (2004) use entropy to measure the degree to which conversations about TV shows are confined to few Usenet groups (low entropy) or are spread out across many Usenet groups (high entropy):

$$\text{ENTROPY}_{it} = - \sum_{n=1}^{N} \frac{\text{POST}_{it}^{n}}{\text{POST}_{it}} \log \left( \frac{\text{POST}_{it}^{n}}{\text{POST}_{it}} \right)$$

Based on the theories above, the authors hypothesize that, conditional on the same volume of word of mouth, conversations that are dispersed across many groups are more likely to result in higher awareness than conversations that are confined within fewer groups. The authors find that more dispersed word of mouth is associated with higher sales (viewership) in the next period, in a model that controls for other factors such as past sales and volume of word of mouth. Hence it is important to consider how information travels in a network when studying the effect of online conversations.

### 30.1.4 Review Dynamics

In the past few years, a number of papers have examined the effect of review dynamics on subsequent review behavior. That is, reviews are not simply independent draws of different opinions, but are in fact correlated across time in predictable ways. The existence of reviewer dynamics has several important implications. First, it calls into question the validity of simple metrics (such as valence, for example) to summarize the current state of word of mouth. Second, if there are consistent biases that arise in reviews due to the dynamics (if, for example, the early reviews are more positive predisposed to the product), and if consumers are not able to control for these biases, the usefulness of reviews may be compromised. Moreover, the firm may need to take actions that
mitigate the biases that are introduced through review dynamics. For example, the firm may design more complicated summary metrics that attempt to de-bias review data or display information in a way that lessens potential biases.

The emerging literature in this area has pursued two objectives: (1) to document the existence of dynamic processes in reviews, and (2) to explain the mechanism behind these processes. We first turn to the question of existence of dynamics. Li and Hitt (2008) demonstrate the existence of an overall negative trend in Amazon book reviews over time, which is surprising given the fact that consumers who purchase the product later on should have more information available to them and are hence expected to make better purchase decisions. Godes and Silva (2011) argue that there are multiple and distinct dynamic processes that are present in consumer reviews. In particular, ratings change systematically over both order and time, and it is important to control for both of these effects. Moe and Trusov (2011) demonstrate the existence of negative autocorrelation in review ratings—an increase in average ratings tends to be associated with subsequent posting of negative ratings. They also show that an increase in rating volume is associated with an increased arrival of negative reviews, and that disagreement between reviewers is associated with fewer subsequent extreme ratings.

The drivers behind these dynamics have been debated. Li and Hitt (2008) argue that the downward trend in reviews arises due to reviewer self-selection, which exists if there is correlation between demand and quality perception. They argue that this correlation results in early product reviewers that are consistently biased compared to the general population. An example of positive correlation is the case where the early buyers of books are also fans of the author's previous books. They find that in a sample of Amazon book reviews the overall time trend is negative, which they interpret as evidence that for books the early reviews are positively self-selected. However, their theoretical model does not imply that the trend need always be negative. In fact, negative correlation between demand and quality perception, which they argue may occur in the case of software where the early buyers are particularly sensitive to defects, would result in a positive time trend.

Interestingly, Godes and Silva (2011) propose another explanation for the negative time trend found in Li and Hitt (2008): all reviews have become more negative over the past decade. In fact, when the authors control for this macro trend, they find that ratings at the book level in fact increase over time. The former (order) effect is driven by the hypothesized mechanism that purchase errors increase as more reviews arrive, and these errors lead to lower ratings. The authors provide support for this mechanism by showing that the sequential decline is bigger when reviewers are very dissimilar from each other. The review context here is also Amazon book reviews.

Moe and Trusov (2011) develop a modeling framework that allows them to separate product ratings into the following components: (1) consumers' independent (or socially unbiased) ratings, (2) the effect of social dynamics, and (3) noise. The review context here is a national retailer of bath, fragrance, and beauty products. Importantly, they show (in a simulation) that social dynamics in reviews may impact the evolution of sales. One interesting simulation result is that a high-quality product may actually
benefit from early mixed ratings, which will result in social dynamics that quickly converge to the true high-level rating. Hence, it is not necessarily the case that marketers need to encourage only positive word of mouth early on.

The emerging literature on review dynamics demonstrates that instead of viewing reviews as independent reports of consumers' experience, it is more accurate to view reviews as pieces of an ongoing conversation between consumers. Note that these dynamics arise largely from the fact that the posting and the timing of each review is under the discretion of each consumer, which implies that reviews are prone to issues of self-selection as well as social dynamics. For example, consider a consumer who had a mildly negative experience at a restaurant. Whether or not she ever shares her opinion may depend on whether she sees a very positive review that contradicts her experience. From the firm's perspective these social dynamics in reviews introduce logistical challenges that relate to simple summary metrics, but, perhaps more importantly, introduce some additional risk since factors other than product quality drive online word of mouth.

In summary, the existing literature provides a rich set of guidelines to firms that want to invest in measuring online conversations. While the academic literature has been somewhat divided on the importance of volume of word of mouth on sales, volume-based measures of conversations have been embraced enthusiastically by industry. For instance, most measures of a company's success in social media are volume-based, such as the number of Facebook followers, number of Twitter followers, and so on. In fact, some company social media measurement communication efforts are exclusively focused on volume-based measures such as the number of mentions or followers on social media platforms. One possible reason behind the popularity of volume-based measures is that these measures are so intuitive—a company page with a million Facebook followers sounds like a very popular and successful page. However, studies such as Godes and Mayzlin (2004) call attention to the fact that volume-based measures may not be useful in all contexts. In particular, a volume-based measure may not provide any new information to the firm that is not already contained in sales. The research cited here suggests that a firm can benefit from collecting a wider range of metrics of word of mouth.

### 30.2 Firm as Influencer

In this role, the firm fosters and shapes social interactions among market participants. (Also see Chapter 12 by Fortin and Boucher on the empirics of network effects, and Chapter 15 by Aral on network experiments.) For example, in order to foster social interactions, the firm may choose to include consumer reviews on its site. The first fundamental question that needed to be addressed is determining whether the effect of social interactions is causal or not. The difficulty associated with identifying
endogenous effects (the "reflection problem") was first pointed out by Manski (1993). For example, suppose that we observe some students in a certain high school adopting a new app, and subsequently their friends adopt the same app. It is difficult to disentangle causality here—it could be that the adoption is due to word of mouth, but it could also be the case that all the students have similar preferences and demographics, and hence are making similar choices across time.

Note that the Manski’s reflection problem is partially solved by obtaining direct word of mouth data. That is, in the example above, if we were to observe that the app adoption was preceded by a recommendation from one student to another, we could rule out that the students are independently adopting the app. However, we would still not be able to rule out that both the electronic communication between high school students and the adoption are influenced by an outside (and an unmeasured) factor. For example, it could be the case that the app targeted advertising at the high school students, which generated both adoption and conversations. Determining that WOM has a causal effect on sales and is not simply correlated with product success is especially important when one considers the firm’s role in managing social interactions through a communication strategy.

30.2.1 The Causal Impact of Word of Mouth on Sales

There are three major approaches that studies have taken in order to demonstrate a causal link between word of mouth and sales. The first approach is a differences-in-differences approach that essentially compares word of mouth and sales across platforms (and across time). The second approach uses instrumental variables to identify the effect of word of mouth on sales. The third approach shows causality through natural experiments.

Let’s first turn to the first approach which utilizes a cross-platform comparison. Chevalier and Mayzlin (2006) examine the effect of Amazon.com and BarnesandNoble.com reviews on book sales. This study is able to address the issue of causality of word of mouth directly. As an illustration, suppose that a new cookbook is heavily promoted by the publisher. This may generate a lot of word of mouth for the book as well as elevated sales. In order to conclude that it is WOM that is driving sales and not another factor such as the underlying quality of the book or the offline advertising campaign (that may be correlated with both WOM and sales), the paper utilizes a difference-in-differences approach: the authors examine the effect of user reviews across BarnesandNoble.com and Amazon.com and across time. That is, the authors examine whether a scathing review of a Julia Child cookbook on Amazon results in the book’s lower popularity on Amazon relative to BN.com. The authors also rule out that

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1 In the marketing literature an influential paper that calls attention to the importance of correctly identifying social effects is Hartmann et al. (2007). Another paper that addresses these issues is Hartmann (2010).
the difference is driven by differences in preferences across sites by differencing across time. As mentioned before, the authors find that reviews have a causal effect on sales, and that the effect is asymmetric: very negative reviews have a bigger impact on sales than very positive reviews.

The second approach to disentangling causality issues when estimating social effects involves identifying the effects through instrumental variables. For example, Shriver et al. 2012 use wind speeds as exogenous variation on windsurfers’ propensity to post content on a windsurfing social network platform. They find that social ties have a positive effect on content generation, and that content generation has a positive effect on obtaining social ties, even when the authors control for endogenous group formation and correlated unobservables.

Finally, a number of studies have used field experiments or natural experiments to demonstrate the causal effect of word of mouth. For example, Chen et al. (2011) use a natural experiment to compare the effect of observational learning (consumers observing what purchases are made by other consumers before them) and word of mouth on sales. The exogenous variation occurs due to the fact that from 2005 to 2007 Amazon removed and then reintroduced a platform feature that displayed what digital camera previous consumers bought after searching a particular model. One interesting result is that, unlike the effect of word of mouth, the positive effect of observational learning (a model sold well in the past) is greater than the negative effect of observational learning (a model did not sell well in the past) on future sales. Another study that utilizes the field experiment approach is Tucker and Zhang (2011). This paper examines the effect of providing popularity information (information on how many previous customers chose to purchase the product) on clicks in a platform that provided wedding service vendor listings. Some of the categories were randomly assigned to display popularity information and some were assigned not to show it. The authors find that the introduction of popularity information results in narrow-appeal vendors receiving more visits than equally popular broad-appeal vendors.

While these studies establish a causal link between social interactions and sales, all deal with “endogenous” or naturally-occurring word of mouth. This leaves open the question of whether it would be possible for the firm to encourage the creation of “exogenous” word of mouth. That is, it is still not clear that the firm would be able to create “buzz” that would result in additional product sales. Godes and Mayzlin (2009) implemented a field study within the context of a “buzz” campaign conducted by a promotional company on behalf of a national restaurant chain. In the field experiment the promotional company recruited a panel of “buzzers” who were encouraged to engage in conversation about the restaurant. The participants self-reported incidents of all interactions. The study also tracked weekly sales of the restaurant chain. This paper finds that indeed the firm is able to generate word of mouth that increases sales. In particular, the study finds that (consistent with Granovetter’s theories), the impactful word of mouth is one between acquaintances (as opposed to conversations between friends). Hence, it is indeed possible for a firm to create word of mouth that meaningfully impacts sales.
30.2.2 Engaging the Right Sender

Consider a firm that plans to influence consumer interactions. The next managerially relevant issue for this firm is the optimal type of word of mouth that it wants to create. For example, does the firm want to engage only certain types of current users? Does it make sense for the firm to target a light or heavy user of the product, or is it perhaps better to target a potential user (and current non-user)? Similarly, does it make sense for the firm to invest in the effort to reach out to an influential user (or an opinion leader), and what is the best way to measure influence?

30.2.2.1 The Sender’s Local Network

A number of papers have examined how the local network of the targeted node impacts the resulting diffusion of information. Interestingly, the results of some of the studies that focus on the network effects are quite counterintuitive in that it is not necessarily the most central and well-connected individuals that are most valuable from the firm’s perspective. For example, consider two studies in this stream. A simulation study by Watts and Dodds (2007) shows that most information cascades are caused by “easily influenced individuals influencing other easily influenced individuals.”

Yoganarasimhan (2012) finds that the size and structure of an author’s local network is a significant driver of the popularity of YouTube videos seeded by her, even after the author controls for video characteristics, seed characteristics, and endogenous network formation. In contrast to Watts and Dodds (2007), this study finds that the marginal benefit of a second-degree friend (a friend of a friend) is higher than that of a first-degree friend (simply, a friend) in the spread of YouTube videos.

30.2.2.2 The Sender’s Loyalty to the Firm

Another possible way to target senders is based on their loyalty to the firm. Godes and Mayzlin (2009) recruit different types of agents as part of the field study on word-of-mouth generation—while some “buzzers” were not initially aware of the restaurant chain (they are from the promotional firm’s panel), others are part of the chain’s loyalty program. In addition, within the loyal customers, there is heterogeneity on how loyal each customer is—while some have just recently signed up to be part of the loyalty program, others visit the restaurant on a regular basis. Interestingly, the paper finds that it is the less loyal customers (including the members of the panel who were not customers of the firm) whose incremental WOM leads to higher sales.

This may at first appear counterintuitive since the more loyal customers are more positively exposed towards the product. The explanation given by the authors for this result is network-based. That is, the less loyal customers are effective in generating incremental profit since their friends and acquaintances have not been previously exposed to information about the product. These results imply that the firm may optimally choose to concentrate on its new customers in spreading word of mouth as part of a viral campaign as opposed to the very loyal customers whose networks have
already been saturated with word of mouth. Another implication of this study is the idea that new customers may be especially valuable to the firm from the perspective of incremental profit since they can spread information to previously unexposed potential customers.

In contrast, Iyengar et al. (2011) find a very different result from Godes and Mayzlin 2009. Iyengar et al. (2011) study the adoption by physicians of a new drug treating a chronic (and potentially lethal) condition. In addition to prescription data, they also collect network data, sales call data, and measures of opinion leadership. The network data is survey-based: each physician is asked to report the names of other physicians with whom she discusses the disease and to whom she refers patients. Each physician is assigned an "in-degree" measure based on nominations by others. Based on prescription volume, the authors are also able to trace product usage. The authors find that connections to heavy users are more influential in driving adoption than connections to light users.

Note that the two studies yield very different managerial implications: Godes and Mayzlin (2009) recommend targeting less loyal customers, who are more likely to be light users, for a viral campaign, while Iyengar et al. (2011) imply that heavy users are particularly important for contagion. There are several possible explanations for the discrepancy in the results. First, the two contexts are very different. The former study deals with restaurant recommendations with low awareness, where credibility of the source may be less important since trial is relatively cheap. The latter deals with a prescription drug with serious side effects where both credibility of the source may be important, and trial is relatively costly. Second, Godes and Mayzlin concerns itself with incremental word of mouth (exogenous word of mouth on top of existing endogenous word of mouth). In contrast, Iyengar et al. deals with endogenous word of mouth, since the authors do not deal with a buzz campaign but are measuring organic adoption. Hence, it could be the case that heavy users are crucial for adoption that is part of endogenous word of mouth and light users are an attractive target for generating incremental word of mouth.

30.2.2.3 Targeting Influential Senders

Another common targeting strategy is to seek out influential senders since they are, by definition, more likely to be persuasive. Of course, before one can answer this question, it is important to define what one means by “influential.” The papers discussed below take different approaches in operationalizing this concept.

One common approach in marketing to measuring influence is to measure the extent to which the sender is an opinion leader using a sociometric scale. For example, the King and Summers’ opinion leadership scale used in Godes and Mayzlin (2009) asks the respondent to fill out the following survey (on a 7-point scale):

1. In general, I like to talk to my friends and neighbors about category (7–very often to 1–never).
2. Compared with my circle of friends, I am _____ to be asked about category (7—not very likely to 1—very likely).

3. When I talk to my friends about category, I (7–give a great deal of information to 1–give very little information).

4. During the past six months, I have told ____ about category (7–no one to 1—a lot of people).

5. In discussions about category (7–my friends usually tell me about category to 1—I usually tell my friends about category).

6. Overall, in my discussions with friends and neighbors about category, I am (7—often used as a source of advice to 1—not used as a source of advice).

Despite the intuitive appeal of seeking out opinion leaders to spread information about the product, Godes and Mayzlin (2009) show that although opinion leadership is useful in identifying potentially effective spreaders of WOM among very loyal customers, it is less useful at identifying less loyal customers. This, along with their finding that it is the word of mouth from less loyal customers that is effective at driving sales, casts some doubt on the usefulness of opinion leadership as a targeting technique.

Iyengar et al. (2011) collect a survey-based measure that aggregates how many other physicians nominate the focal physician as someone with whom they discuss the disease or to whom they refer patients (this measure is referred to as “in-degree”) in addition to a survey-based measure of own-opinion leadership. Hence, the former is based on others’ reports of the focal doctor’s opinion leadership, while the latter is self-reported. The authors also find that sociometric and self-reported measures of leadership are weakly correlated and associated with different effects: physicians with higher in-degree adopt earlier, while physicians who rank higher on the self-reported leadership measure of leadership adopt earlier but are less sensitive to contagion from peers.

Another interesting approach to identifying influential consumers is undertaken in Trusov et al. (2010). The authors propose to identify the influence of a social network member by examining the effect that the user has on her friends’ behavior. In particular, if a member increases her usage and the people connected to her also increase their usage, they identify this person as influential. Conversely, if a member’s usage does not impact her friends’ behavior, the authors infer that this person is not influential. Interestingly, the authors find that an increase in the number of connections does not necessarily imply that the user is influential.

In summary, a firm that seeks to influence social interactions can be reassured that such an undertaking is possible—the literature has shown that organic word of mouth has a causal effect on sales and that it is possible for the firm to help create social interactions that will impact sales. In addition, the literature gives some guidance on the types of senders that should be targeted if the firm seeks to generate exogenous word of mouth. In particular, in cases where awareness is low, the firm needs to target its less loyal customers since their networks are less saturated with information about the product. Finally, while opinion leaders are more likely to adopt earlier, opinion leaders may be less useful if the firm seeks to generate word of mouth from less loyal customers.
30.3 Firm as Participant

30.3.1 Content Creation versus Linking

Finally, the most active role that the firm can play in managing social interactions is to actually participate in consumer conversations. For example, the firm can post its views on a corporate blog, inviting and responding to comments and feedback. One key question here is how the firm’s posting and linking behavior affects the size of its audience. Mayzlin and Yoganarasimhan (2011) analyze the role of links to other blogs as signal of blog quality. This paper models bloggers as producers of information (or “breaking news”), and readers as consumers. By linking, a blog signals to the reader that it will be able to direct her to news in other blogs in the future. The downside of a link is that it is a positive signal about the rival’s news-breaking ability. Hence, one action (a link) sends multiple signals to the reader: a positive signal about the quality of a focal blog as well as a positive signal about the quality of a potential rival. The paper shows that linking will be an equilibrium outcome when the heterogeneity on the ability to break news is low relative to the heterogeneity on the ability to find news in other blogs.

Several empirical papers have analyzed the value of links, and the connection between link formation and content generation. As mentioned before, Shriver et al. (2012) find that social ties have a positive effect on content generation, and that content generation has a positive effect on obtaining social ties. Stephen and Toubia (2010) find that in an online marketplace with links between various sellers, an increase in links creates economic value for the marketplace. In particular, the authors find that an increase in links between marketplace members is associated with an increase in commission revenue for the firm that runs the marketplace. In contrast, growth in the number of dead-end shops has a negative effect on marketplace performance. All of these papers suggest that both linking and content generation are important and productive activities.

Another option for firms is to manipulate conversations surreptitiously by exploiting the anonymity afforded by online communities. This approach raises some fundamental questions regarding the viability of online word of mouth since a large amount of this kind of promotion would undermine the credibility and, thus, usefulness of online conversations. Mayzlin (2006) examines this blurring of the lines between advertising and word of mouth. This paper develops a game-theoretic model where two products are differentiated in their value to the consumer. Unlike the firms, the consumers are uncertain about the products’ quality. Firms have the option of posting anonymous, positive reviews about their product. One question that immediately arises is whether, given this anonymity and the firms’ obvious self-interest, consumers would be influenced by online reviews. Broadly speaking, as more and more consumer purchases are being influenced by reviews posted by anonymous others and as the
incentive grows for firms to surreptitiously manipulate these reviews, should consumers in equilibrium continue to place faith in them? In a unique equilibrium where online word of mouth is persuasive, the paper concludes that the answer is yes. In this equilibrium, firms spend more resources promoting inferior products: the firm with the better product optimally free-rides on unbiased word of mouth.

Dellarocas (2006) also develops an analytical model of strategic firm manipulation of online forums. This paper finds that manipulation may increase the quality of information provided by an online forum, which is the case if the amount of manipulation is increasing in the quality of the firm. Importantly, this paper points out that the development of “filtering” technologies makes it costlier for firms to manipulate online word of mouth.

Mayzlin et al. (2014) undertakes an empirical analysis of the extent to which manipulation occurs and the market conditions that encourage or discourage this activity. Specifically, this paper examines hotel reviews, exploiting the organizational differences between two travel websites: Expedia.com and TripAdvisor.com. That is, while anyone can post a review on TripAdvisor.com, a consumer could only post a review of a hotel on Expedia.com if she actually booked at least one night at the hotel through the website. Thus, the cost of posting a fake review on Expedia.com is quite high relative to the cost of posting a fake review on TripAdvisor.com. We show that the differences in the distribution of reviews for a given hotel between TripAdvisor.com and Expedia.com are affected by the firm’s incentives to manipulate. Note that while several papers in marketing and computer science/IT journals have attempted to empirically document the existence of manipulated reviews, the methodology proposed in this paper avoids the challenge of classifying individual reviews as fake, and instead uses differences between sites to infer manipulation. The authors find evidence that supports the existence of manipulation, and the amount of manipulation is greater for small owner properties.

30.4 Conclusion and Future Directions

A firm that seeks to manage consumer social interactions can turn to a growing academic literature that directly addresses issues related to observing, influencing, and participating in consumer conversations. Despite the progress made so far, there are a number of outstanding issues that have yet to be addressed by researchers.

One potentially interesting area for exploration is the extent to which consumer motivation to talk has strategic implications on how the firm can manage consumer interactions. For example, Godes and Wojnicki (2014) demonstrate that consumers that are experts in a domain generate word of mouth that is positively biased since the valence of their experience signals their ability to make good choices. That is, a consumer that is a “foodies” may be more eager to share a positive experience (“a wonderful hole-in-the-wall Indian place I found”) than a negative experience (“a
terrible pizza joint”). One possible implication of this finding for a new product is that sampling by an expert is especially desirable—not only is the word of mouth generated potentially more persuasive due to the sender’s expertise, but this consumer is positively biased.

Another area for exploration is the extent to which firm’s traditional marketing actions impact organic word of mouth. Campbell et al. (2015) show that advertising for a new product may decrease the amount of organic word of mouth and information acquisition. In this model consumers engage in word of mouth in order to signal to others that they are high types who have lower costs of information acquisition. By advertising the firm reduces the asymmetry between high and low types, which reduces the signaling value of word of mouth, and hence decreases the amount of information acquisition.

Next, consider a firm that is considering response to negative word of mouth. To what extent does a public response lend legitimacy to the original consumer sentiment? Is the firm sometimes better off keeping silent on a negative rumor? How are these considerations affected by whether the rumor is true or false?

Finally, most of the papers reviewed here tend to examine firm optimal actions in isolation. Consider the targeting of particularly attractive senders by firms. A sender who is well-placed on a network is likely to appear to be a good target to multiple firms, which implies that the competition will be greater for certain types of senders. How does this increased competition affect optimal targeting? Does it make sense for firms to differentiate on whether they target the central versus the more fringe senders of information?

References


