Finding Influencers and Consumer Insights in the Blogosphere

Naohiro Matsumura
Osaka University
1-7 Machikaneyama,
Toyonaka, Osaka
81-6-6850-5231
matumura@econ.osaka-u.ac.jp

Hikaru Yamamoto
Seikei University
3-3-1 Kichijoji-kitamachi,
Musashino-shi, Tokyo
81-422-37-3580
yamamoto@econ.seikei.ac.jp

Daisuke Tomozawa
NIFTY Research Institute
6-26-1 Minami Oi,
Shinagawa-ku, Tokyo
81-3-5471-3706
tomozawa.daisuke@nifty.co.jp

Abstract

In this paper, we attempt to specify the influencer and the influential terms in consumer package goods by using the influence diffusion model (IDM). IDM calculates the spread of a term in the blogosphere recursively, and evaluates the influence of terms, blog entries, and bloggers. The model was applied to the official data from a blog hosting service. The results of the model were compared with the term frequency (TF). Then, the influencers of the IDM were examined and compared with the results of other network indices such as number of links and trackbacks. The results indicate that IDM performs better in finding blogs posted by bloggers with product usage experience or with an interest in the product. A propagation network which visualizes the consumer-oriented key marketing elements is also presented. An empirical analysis suggests the validity of IDM for marketing decision marking.

Introduction

Recent developments on the Internet such as weblogs and social media enable consumers to share their consumption experience with others. Such product information transmitted by individuals to individuals is called word-of-mouth (WOM). According to the Word-of-Mouth Marketing Association (WOMMA), WOM is defined as "the act of a consumer creating and/or distributing marketing-relevant information to another consumer."

The volume of WOM and personal influence are rapidly growing because of the emergence of user generated media (UGM).

This change in environment affects not only consumers, but also marketers. Marketers are faced with a new challenge, i.e., to measure WOM in the blogosphere and utilize the results for marketing decision making. The central interests of marketers are: who talks about the product? Who is influenced by WOM? What do consumers like/dislike about the product? Which marketing element is perceived to be relevant to consumers? Which communication messages successfully reach consumers?

This paper attempts to answer these questions. The aim of our research is (1) to identify influencers who write blogs which influence other bloggers and (2) to identify the key marketing elements which diffuse via WOM communication in the blogosphere.

This paper is organized as follows; related research in the area of personal influence is discussed in the next section. After that, we formalize the proposed model, called the influence diffusion model (IDM). An overview of the data is then presented, followed by empirical analysis and conclusions.

Related Work

The consumer's purchase decision making is often influenced by WOM. The researches by Arndt (1967), Engel, Blackwell, and Kegerreis (1969), and Day (1971) are examples of early studies suggesting the role of WOM as a driver of buyer behavior. Because the sender of WOM is independent of the market, consumers perceive him or her to be more reliable, credible, and trustworthy compared with firm-initiated communications (Arndt 1967; Bickart and Schindler 2001).

The basis of past WOM research is that WOM has an impact on consumer behavior. However, all WOM is not created equal. There are consumers who have the ability to create more marketing-relevant information and to spread it to a larger circle of friends. These special consumers have attracted researchers' attention for decades. For example, Lazarsfeld, Berelson, and Gaudet (1948) found "opinion leaders", who actively gather information sent from the mass media, add their own views and values to this information, and then pass it on to consumers around them in daily life. To identify these special consumers with extraordinary skills, most of the marketing and sociology literature has employed self-reported, one-shot questionnaires to identify opinion leaders (Childers 1986; King and Summers 1970; Rogers 1962).

A number of studies have employed social network analysis to capture the social structure and diffusion process of WOM. For example, Reingen and Kernan (1986) documented the relationship between the flow of information and the tie strength. Brown and Reingen (1987) employed the relational properties of tie strength and homophily to examine referral behavior. These researchers conclude that social ties serve as a "pipeline" for transferring product-related information.

Because the early marketing literature analyzed social relations in the offline environment, the sample size was small, the data was qualitative, and the network was analyzed as a static snapshot (Dwyer 2007).

On the other hand, computer science literature analyzes link behavior with large-scale online data and focuses on the network structure (Herring et al. 2005; Kumar, Novak, and Tomkins 2006; Marlow 2004).

Most of such computer science research focuses on the quantitative properties of the nodes, such as number of comments and incoming links (Mishne and Glance 2006). Not much attention is paid to the attributes of blog content or the attributes of the consumer posting the blog, such as degree of interest in the category, level of product knowledge, the stage of consumer purchase behavior.

In addition, much work has been devoted to studying the influence of nodes in the blogosphere. Such influence is expressed with various terms such as infection, cascade, or diffusion. In this research, the presence of link relations or comment relations is often used as indicators of influence (Java et al. 2007). While the link relation together with a time stamp provides a good starting point for the analysis of influence, more accurate evidence of personal influence is desirable for marketing purposes.

For a more precise definition of influence, some researchers have investigated the qualitative aspects of blog messages, such as URL mentioned in the posting (Adar and Adamic 2005; Furukawa et al. 2007). Inspired by these studies, we decided to use the appearance of the same term in postings with link relations as evidence of influence.

This paper proposes an alternative approach to identify influencers, that is, to capture the quantitative and qualitative aspects of the influencer simultaneously. In the next section, we explain our model for identifying influencers and influential terms.

Influence Diffusion Model

Our model is called the influence diffusion model (IDM). IDM was originally an algorithm for measuring values of influence of messages, senders, and terms from online bulletin boards (Matsumura 2003). Recently, the algorithm was revised and expanded to measure values of influence to identify human influence networks (Matsumura 2005; Matsumura, Goldberg and Llor'a 2007, Matsumura and Sasaki 2007).

Throughout this paper, we use the term "blogger" to mean an individual who keeps and updates a blog. We use the term "postings" as an entry created by a blogger on his or her blog.

IDM calculates the spread of a term in the blogosphere recursively, and evaluates the influence of terms, blog entries, and bloggers. Figure 1 depicts a simple inter-blog posting relationship.

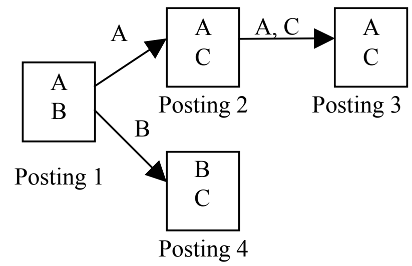

Figure 1. The process of influence diffusion

Posting 1 contains terms A and B, and posting 2, which was posted after Posting 1 and has a link relation (expressed as "edge") and contains terms A and C. In such a situation, we assume that term A propagated from posting 1 to posting 2. The arrow represents the propagation of the terms. Our assumption is that if the same term appears in all of the postings connecting the two postings with link or trackback, the blog posted later was "influenced" by the first blog.

Let's denote the set of terms included in postings 1, 2, 3, and 4 as w_1, w_2, w_3, w_4. The number of terms propagating from a posting x on a posting y (x precedes y) is defined as

$$n_{x\rightarrow y} = |w_x \cap \cdots \cap w_y| \quad (1)$$

Here, $|w_x \cap \cdots \cap w_y|$ represents the number of terms which appear in all postings between posting x and posting y. Using Formula (1), the number of propagating terms in Figure 1 is calculated as follows:

$n_{1\rightarrow 2} = |w_1 \cap w_2| = 1$
$n_{1\rightarrow 3} = |w_1 \cap w_2 \cap w_3| = 1$
$n_{1\rightarrow 4} = |w_1 \cap w_4| = 1$
$n_{2\rightarrow 3} = |w_2 \cap w_3| = 2$
$n_{others} = 0$

Next, we define the influence of posting x, denoted as i_x, as the sum of propagating terms in the blogosphere.

$$i_x = \sum_{y \in all\_postings} n_{x\rightarrow y} \quad (2)$$

Then the influence of each posting, i_1, i_2, i_3, i_4 is calculated as follows:

$i_1 = n_{1\to2} + n_{1\to3} + n_{1\to4} = 1 + 1 + 1 = 3$
$i_2 = n_{2\to3} = 2$
$i_3 = 0$
$i_4 = 0$

Bloggers often read other bloggers' postings when writing their own blogs. The incoming influence of posting x, denoted as j_x, can be measured as the sum of terms influenced by other postings.

$$j_x = \sum_{y \in all\_postings} n_{y\to x} \quad (3)$$

This can be considered to be the bloggers' ability to gather information and utilize other blogs as information sources for his or her blogs. The power of influence acceptance of each posting, j_1, j_2, j_3, j_4, is calculated as follows:

$j_1 = 0$
$j_2 = n_{1\to2} = 1$
$j_3 = n_{1\to3} + n_{2\to3} = 1 + 2 = 3$
$j_4 = n_{1\to4} = 1$

The influence of four postings in Figure 1 is summarized in Table 1. *Px* denotes the postings.

	P 1	P2	P3	P4	i_x
P 1	0	1	1	1	3
P 2	0	0	2	0	2
P 3	0	0	0	0	0
P 4	0	0	0	0	0
j_x	0	1	3	1	5

Table 1. # of Terms propagating among postings

The influence of each blogger can be measured using the influence of postings. Let's denote the blogger who wrote posting 1 as S_a and the author of posting 2 as S_b, and let's assume that the same blogger, S_c, posted postings 3 and 4 . The influence of blogger S_x can be considered to be the sum of influences of his or her postings, as shown in Formula 4.

$$I_x = \sum_{y \in all\_postings\_by\_x} i_y \quad (4)$$

The influences of bloggers S_a, S_b, S_c, which are I_a, I_b, I_c respectively, are calculated as follows:

$I_a = i_1 = 3$
$I_b = i_2 = 2$
$I_c = i_3 + i_4 = 0$

Similarly, the blogger's ability to read and utilize information in other blogs, denoted as J_x, can be considered to be the sum of incoming influences. J_x is calculated as follows:

$$J_x = \sum_{y \in all\_postings\_referred\_by\_x} j_y \quad (5)$$

$J_a = j_1 = 0$
$J_b = j_2 = 1$
$J_c = j_3 + j_4 = 3 + 1 = 4$

Table 2 summarizes the outgoing / incoming influences of a blogger .

	Inf(out)	Inf(in)
S_a	3	0
S_b	2	1
S_c	0	4

Table 2.Outgoing / Incoming influences of each blogger

One of the advantages of IDM is that only the propagated terms among link relationships are counted. It captures frequent terms since they have a better chance to be propagated. IDM also picks up infrequent terms that are considered to be valuable by consumers.

The influential terms are those which are screened by consumers. Only truly valuable terms that reflect consumer insight "survive" and propagate in the blogosphere. IDM is indigenously qualitative, because the qualitative aspects of a term are evaluated by consumers when they read another consumer's blogs. In our definition, bloggers who use influential terms in their postings are "influencers".

Next, we define the influence of terms. The function describing whether a posting appearing between postings x and y through link and trackback contains term A or not is defined as follows:

$$\delta_{x\to y}(A) = \begin{cases} 1 \text{ if } \{w_x \cap \ldots \cap w_y\} \text{ contains A} \\ 0 \text{ otherwise} \end{cases} \quad (6)$$

The influences of the terms *A, B, C* are calculated as follows:

$K_a = \delta_{1\to2}(A) + \delta_{1\to3}(A) + \delta_{2\to3}(A) = 3$
$K_b = \delta_{1\to4}(B) = 1$
$K_c = \delta_{2\to3}(B) = 1$

We applied IDM to data provided by a blog hosting service and identified influential postings, influential bloggers, and influential terms.

Data Overview

Topic of Analysis

The data was provided by NIFTY Research Institute, which is a division of NIFTY Corporation, one of the largest Japanese Internet service providers. NIFTY Research Institute offers BuzzPulse, a blog mining and consulting service to advertisers. One of the competitive advantages of this service is its coverage. It collects over 200 million blogs, approximately 90% of all blogs in Japan. In order to find the influencer and their consumer insight and to gain insight into future decision making by specifying unique selling points, we analyzed the diffusion of market-relevant information on "Tsubaki" ("camellia" in Japanese), a new shampoo product from the Shiseido corporation. The reasons for selecting the shampoo category in 2006 are as follows: (1) it's a 1.3 billion dollar market [1]; (2) it's the largest category in advertising expenditure in Japan[2]; and (3) a dramatic change occurred in marketing competition due to the launch of this product.

Tsubaki was launched in March and emerged no.1 in the 2006 shampoo sales ranking.

Shiseido spent a record-breaking 46 million dollars in marketing and hired celebrities to push the product. TV, magazine, and billboard ads featured top models and actresses in Japan. It also hired a popular vocal group to perform an original song, which became a huge hit. The key message of the advertising campaign was that "Japanese women are beautiful", a counter plan against the Unilever corporation which has historically featured Hollywood celebrities as endorsers.

Data Description

Our aim here is to analyze the flow of information and find the influencers and successful marketing elements for this product.

In order to achieve our goal, BuzzPulse collected blogs posted between March to August 2006. Then, blogs containing the term "Tsubaki" were screened. A total of 10,864 postings were used for the analysis. These postings were manually investigated by the staff of NIFTY Research Institute to classify them by the stage of consumer purchase behavior.

Among the 10,864 postings, 2,763 postings were classified as "customer"; i.e., the blogger actually purchased the product. 3,952 postings were tagged as "potential customer", meaning the postings talked about the product but did not reach the stage of purchase. 38 postings were "unknown", 357 postings could not be opened, and 3,754 postings were irrelevant. These irrelevant postings contained the term Tsubaki but were different meanings used in different contexts, such as Tsubaki (camellia) flower in the context of gardening, or simply splogs.

As stated in the previous section, we consider the posting is "influenced" when two postings have link or trackback relations, and it uses the same term appearing in the posting written earlier. For this reason, we obtained link/trackback relationships among the postings. There were a total of 3,744 links among postings, and the average number of links per posting was 0.35. There were 854 trackbacks, and the average number of trackbacks per posting was 0.08.

The blogs were written in Japanese. Before applying IDM to the blog data, we first used MeCab [3], a morphological analysis system. We used nouns, verbs, adjectives, and their composite as "terms" for the analysis in the next section. To improve the accuracy of the measurement, noise terms (or "stop terms" (Salton and McGill 1983)) were removed. A list of noise terms was made in advance, from a discussion with marketing consultants.

Empirical Analysis

Influential Terms, Postings, Blogs

We applied IDM to the data provided by the blog hosting service to identify the influencers and their consumer insights.

Table 3 lists the top 20 terms ranked by term frequency and by influence in IDM. The column "Inf" shows the number of propagations in IDM; "diff in ranking" shows the difference in rank between the two.

Terms captured in IDM are marketing-relevant terms such as "damage", "coating", "repair", which are related to the functional benefits of the product. Also, "camellia oil" ranks 20th, which is the main component and the unique selling point of the product. These marketing-relevant terms would not be in the top ranks if IDM were not applied.

The influential terms in IDM are those that were considered relevant by the consumer; thus, they reflect consumer insights and can be interpreted as key marketing elements. IDM enables the marketer to identify consumer-oriented unique selling points, which are valuable for building an advertising strategy. The difference in rank between TF and IDM shows the uniqueness of our model. Average rank differences are 162 (top 10), 508 (top 30), 1075 (top 50) and 1447 (top 100).

As can be seen in Table 3, there are overlaps in the ranking. The overlap percentages are 0.50 (top 10), 0.60 (top 30), 0.46 (top 50), and 0.42 (top 100). These overlaps show that IDM also captures frequent terms, which are important in the "buzz" volume.

[1] As of 2006

[2] Classified as "cosmetics/toiletries" categories in Dentsu (2007) Advertising Expenditure in Japan http://www.dentsu.com/marketing/pdf/expenditures_2006.pdf

[3] http://mecab.sourceforge.net/

	Term	TF	Term	Inf	diff in ranking
1	Shiseido	3182	Shiseido	970	0
2	shampoo	2921	CM	532	1
3	CM	2820	feeling	375	1
4	feeling	2162	shampoo	155	-2
5	like	2035	effect	146	20
6	me	1609	SMAP	140	1
7	SMAP[4]	1556	special	129	520
8	product	1344	classification	129	950
9	woman	1270	series	126	123
10	on sale	1221	photo	83	4
11	fragrance	1160	starring in CM	76	17
12	expect	1156	damage	72	1439
13	actress	1041	official site	70	2860
14	photo	991	coating	70	1986
15	skincare	821	friend	68	6
16	work	818	like	65	-11
17	use	791	repair	62	446
18	news	786	conditioner	58	9
19	time	775	new arrival	57	20
20	name	704	camellia oil	57	126

Table 3.Top terms by term frequency and term influence

	Posting	Inf(out)	Inf(in)
1	http://1tsu..	187	16
2	http://1tsu..	143	10
2	http://1tsu...	143	10
2	http://1tsu...	143	10
2	http://1tsu...	143	10
6	http://b003...	142	7
7	http://1tsu...	137	11
8	http://1tsu...	118	9
9	http://1hear...	93	17
10	http://blog.l...	89	3

Table 4. Top postings by outgoing influence

	Blogger	Inf(out)	Inf(in)	Posting	link
1	http://1tsu...	1020	1302	14	84
2	http://1tsu...	801	436	16	130
3	http://b003...	358	276	6	25
4	http://b001...	150	283	6	21
5	http://blog.l...	138	24	3	9
6	http://b004...	115	91	2	3
7	http://1hear...	111	194	3	26
8	http://morn...	97	0	2	15
9	http://jean...	97	178	25	49
10	http://knty...	94	52	2	6

Table 5. Top bloggers by outgoing influence

[4] Name of the popular vocal group which performed the original CM song.

	Blogger	Inf (out)	Inf (in)	Posting	link
1	http://1tsu...	1020	1302	14	84
2	http://1tsu...	801	436	16	130
3	http://b001...	150	283	6	21
4	http://b003...	358	276	6	25
5	http://amebl..	10	210	2	11
6	http://1hear..	111	194	3	26
7	http://www.b	79	186	2	16
8	http://jean...	97	178	25	49
9	http://shise...	55	123	13	4
10	http://1hear..	115	91	2	3

Table 6. Top bloggers by incoming influence

Tables 4, 5, 6 list the influencers and influencees. The URLs of the bloggers are masked to protect their privacy. Table 4 lists the top 10 influential postings, their outgoing influence (Inf (out)) and incoming influence (Inf (in)). Table 5 shows the top 10 influential bloggers on Tsubaki, and Table 6 shows the top 10 influencees. These bloggers actively checked and read other bloggers postings and imported the ideas and terms to their blogs.

The overlap of the bloggers in Table 5 and Table 6 indicates that influential bloggers are also consumers who are active in collecting other consumer's usage experiences.

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IDM vs. Links and Trackbacks

Next, we compare the results of IDM against the quantitative aspect of influencers in the network structure. Our questions are, are the influencers important nodes in the social network in the blogosphere? Are frequently used network measures important features when identifying marketing-relevant influencers?

To tackle these questions, we investigated the number of links and trackbacks and compared them with the measures of IDM.

We once again used the results of manual classification of the postings and calculated the proportion included in the top 100 postings of each measure. The definition of "customer", "potential customer", "irrelevant", and "cannot open" are stated in the previous section.

Table 7 shows the results of the comparison. For example, if we take the most-linked postings, only 5% are postings by consumers who purchased the product, 7% are by potential customers who mentioned the product but do not indicate the purchase, and 88% of the postings are irrelevant in the context of marketing.

On the other hand, if we take the top 100 postings which emerge as the result of IDM, the percentage of irrelevant postings dramatically decreases.

	Link	TB	Inf (out)	Inf (in)
Customer	0.05	0.09	0.14	0.22
Potential customer	0.07	0.40	0.61	0.51
Irrelevant	0.88	0.42	0.21	0.25
Cannot open	0.00	0.09	0.04	0.02

Table 7 Network structure measures vs. IDM

	Link	TB	Inf (out)	Inf (in)
Customer	0.18	0.13	0.19	0.24
Potential customer	0.39	0.45	0.55	0.48
Irrelevant	0.41	0.37	0.23	0.26
Cannot open	0.02	0.05	0.03	0.02

Table 8 Network structure measures vs. IDM

For example, if we take the top 100 influential postings, 14% are customers and 61% are potential customers. The percentage of customers increases even more if we look at the top 100 influencees.

Table 8 shows the results of comparison at the blogger level. We can see similar results as those in Table 7.

Segmentation of Consumers in the Blogosphere

There are two key measures of influence in IDM: Inf (in) and Inf (out). Bloggers who write postings that are high in Inf (out) are those who influence more than others, and bloggers who write postings that are high in Inf (in) are those who are influenced more than others. The former category are bloggers who use terms which propagate in the blogosphere, and the latter are the bloggers who are eager to check and read other bloggers' postings and use the terms in his or her blogs. In this subsection, we segment the consumer by these two indices. This segmentation of consumers is a promising tool for influencer marketing and customer relationship management (CRM). Table 9 illustrates the results of the segmentation. The posting is classified as "high" if it is included in the top 100 of incoming/outgoing influence, and "low" otherwise.

Low Inf (out), High Inf (in) Customer 0.18 Potential customer 0.56	High Inf (out), High Inf (in) Customer 0.31 Potential customer 0.38
Low Inf (out), Low Inf (in) Customer 0.25 Potential customer 0.36	High Inf(out), Low Inf (in) Customer 0.07 Potential customer 0.70

Table 9 Matrix of influencers and influencees

The percentage of potential customers is high in the upper left hand corner (0.56) and lower right hand corner (0.70). This suggests that there are two types of potential customer: active seekers and active speakers of the product information. The consumers in the upper right hand box are influencers who actively gather other consumer's postings. The percentage of consumers is highest among the four categories, suggesting that these bloggers have high outgoing influence due to their product usage experience. The postings of influencers are not based on speculation, but based on the actual product usage experience.

The Propagation Network of USP

One of the outputs of IDM is the visual presentation of term propagation. We visualized the propagation network by using the top 100 terms which appear in both the TF ranking and the influence ranking of IDM. As explained in the earlier section, IDM captures the terms that are passed on to other consumers. These terms are propagated because consumers perceive them to be relevant. Thus, the propagation network represents the unique selling point (USP) reflecting the consumer insight.

Each node represents the term, and the edge is drawn when there is an influence. We consider that a term does not appear by itself, but is influenced to some extent by other bloggers. For example, in Figure 3, the term "TV" did not emerge by itself; it was partly influenced by the prior topic, "starring in TVCM". The term with an outgoing edge can be considered to be the trigger or stimulator of other terms.

Three clusters emerged in the IDM results. Figures 2, 3, and 4 represent the term propagation in each cluster. The top 10 influential terms are highlighted in gray.

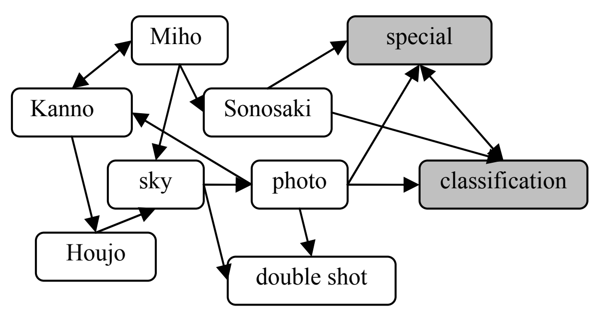

Figure 2. Term propagation in cluster 1

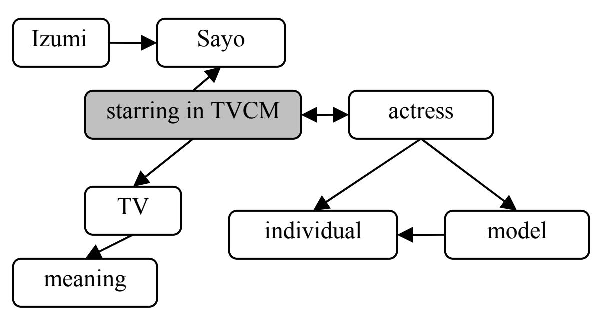

Figure 3. Term propagation in cluster 2

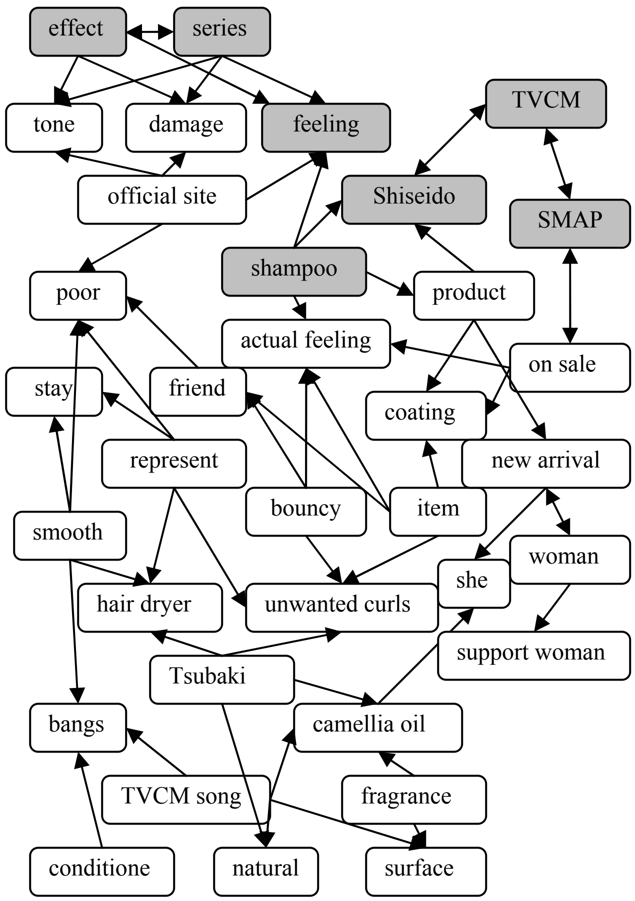

Figure 4. Term propagation in cluster 3

The terms which appear in Cluster 1 do not have a strong relationship with our subject, Tsubaki. The capitalized terms are the names of female celebrities. "Izumi" and "Sayo" are celebrities starring in the Tsubaki advertisement. However, the characteristics or the benefit of the product do not appear in this cluster.

In contrast, the terms in Cluster 2 are more related to the product. The bloggers in this cluster are interested in Tsubaki and its advertisement as entertainment news, not as a hair care product.

Cluster 3 is the largest cluster, and most of the terms in this cluster are highly marketing-relevant. It contains terms that would not appear without product usage experience, such as "fragrance", "smooth", and "bouncy". It also contains the communication message of the advertisement, which is to support women and encourage them to have confidence. The terms indicating the functional benefits of the shampoo, such as "smooth", prevents "unwanted curls", has a "coating", and repairs "damage" also propagated in this cluster.

These results indicate the success of the product. The marketing elements such as characteristics and the functional benefit effectively reached the target audience and diffused in the blogosphere via WOM. We can infer that the reason this product acquired the number 1 position in the shampoo category is due to the successful marketing communication and spread of desirable WOM.

The flow of diffusion in cluster 3 can be interpreted as follows; there are three main topics in this cluster: (1) the topic triggered by the "official website" of the product in the upper left, (2) a topic triggered by advertisements in the upper right hand corner, and (3) the usage experience related topic at the bottom of Figure 4.

Topic (1) is clustered around the conversation on the official website and has a weak connection with other topics. In topic (3), there are discussion starting points, such as "smooth" and "bouncy", and discussion goals, such as "hair dryer", "unwanted curls", and "bangs". The "Actual feeling" of product usage is the theme on which topics (2) and (3) merge into each other.

For marketers, this propagation network can be used as a visual summary of consumer's word-of-mouth in the blogosphere. The terms that appear in this propagation network are influential terms that reflect consumer insight, and the result can be used for strategic decision making since these are consumer-oriented key marketing elements.

Conclusion

In this paper, we identified influential postings, influential bloggers, and influential terms by using the influence diffusion model (IDM). The influencers of IDM were examined and compared with other quantitative aspects of nodes in the network structure. The results suggest that when identifying marketing-relevant influencers, IDM is more effective than frequently used network related indices such as number of links and trackbacks. Finally, a propagation network that visualizes consumer-oriented key marketing elements was presented. The empirical analysis suggested the validity of IDM for marketing decision marking.

Future work will include examination of the model in other categories, evaluating the model statistically toward formalization, prediction of WOM behavior, and customization of the model for advertising media evaluation and planning.

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