Computational Approach to Prediction of Attitude Change Through eWOM Messages Involving Subjective Rank Expressions

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***Abstract*— Electronic word-of-mouth (eWOM) is an important information source that influences consumer product evaluations. This paper presents a computational model that predicts the potency-magnitude relations of eWOM messages involving subjective rank expressions, which refer to the linguistic representations related to the attitude-levels of the benefits of the product attributes. The amount of required inference for the message receiver to know the attitude-level through the message is quantified as *inference quantum* by using *inference space*, which is characterized by two evaluation parameters: evaluation target size and evaluation scale size. The computational model incorporates the idea of inference quantum into the cognitive hypotheses that were developed to account for the potency differences with reference to the expertise levels - experts or novices - of the message receiver of the products.**

By applying the computational model to simple eWOM messages, the potency-magnitude relations were observed to depend critically on the values of the message receiver's evaluation parameters. This paper defines three message-classes, which are also studied in the areas of opinion mining and sentiment analysis, and investigates mathematically how the potency-magnitude relations change based on the values of the evaluation parameters.

***Index Terms*— cognitive modeling; attitude change; electronic word-of-mouth; ewom; social media**

I. Introduction

In recent years, there has been a focus on electronic word-of-mouth (eWOM) as the information source that influences consumer product evaluations [1]–[3]. eWOM messages refer to statements that are posted electronically in social media such as bulletin boards on the Web. The content includes other consumers' product evaluations and recommendations based on their own experiences and preferences. What kinds of eWOM messages have large potency on the product evaluations made by the consumer who is exposed to the messages? If we can predict the potency on an individual basis, then it will be possible to create an intelligent agent to selectively provide effective statements to individual consumers from among the huge volumes of diverse eWOM messages on the Web. These kinds of intelligent agents would increase opportunities to use eWOM messages and could be expected to promote interactions between consumers via the Web.

The author previously proposed cognitive hypotheses that account for the potency differences in two types - *comparison* and *degree* - of eWOM messages involving subjective rank expressions [4]. This paper develops a computational model of the hypotheses to apply them to various types of messages obtained using techniques from opinion mining and sentiment analysis [5], [6]. The following are the contributions of this paper:

1) Modeled eWOM messages with reference to comprehensive message typology in the areas of opinion mining and sentiment analysis.
2) Developed a computational model that predicts the potency-magnitude relations between two eWOM messages involving subjective rank expressions.
3) Investigated mathematically how the potency-magnitude relations change based on the values of the message receiver's evaluation parameters.

Although the former two contributions were previously presented [7], this is the first appearance for the last contribution (Section V.). In addition, this paper includes four minor modifications from previous work: (1) the idea of "attitude" [8], [9] is incorporated into the definition of subjective rank expressions to clarify the meaning of the "levels" of consumer evaluations (Section II. A.); (2) detailed descriptions of the research background are given (Sections II. B. and C.); (3) the inference quantum is redefined based on the idea of entropy in the inference spaces (Section IV. B.); and (4) computational examples are revised so that two cases with different values of evaluation parameters can be compared (Section IV. C.).

In the following, Section II describes the background of the current research. Section III develops the models of eWOM messages involving subjective rank expressions. Section IV formalizes the computational model and illustrates the prediction processes with example messages. Section V investigates mathematically how the potency-magnitude relations change based on the values of evaluation parameters. Section VI concludes the paper and describes the future work.

II. Background

A. Subjective Rank Expressions

Research on word-of-mouth (WOM) communication, which Arndt defined as the oral person-to-person communication between a receiver and a communicator that the receiver perceives as non-commercial [10], has been conducted for many years [11]. It ranges from the motives

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for the communications [12], [13] to the effects on the receivers' purchase decisions [14], [15]. Recently, the widespread penetration of social media has increased interest in eWOM communication researches (e.g., [16], [17]) that differ from traditional WOM researches in that they focus on the more detailed aspects of the information content [1], [3].

Lee et al. introduced a differentiation between objective attributes such as size and weight and subjective attributes such as color and shape [1]. Park et al. divided eWOM messages on product attributes into two types, which are "attribute-centric" and "benefit-centric," and verified the differences in the potency of these two types [3]. In contrast, this paper focuses on *subjective rank expressions*, which are related closely to researches in opinion mining and sentiment analysis. Here, subjective rank expressions refer to the linguistic representations related to the attitude-levels of the benefits of the product attributes [4]. A benefit and product attribute pair to be evaluated is called "target" in this paper. The attitude-levels of a target means its ranks or grades with respect to personal attitudes [8], [9]. Thus, subjective rank expressions focus on the benefits and the product attributes that are used as two basic elements to represent product evaluations based on the perspectives in consumer behavior research [18], [19]. The idea of subjective rank expressions is shown in Fig. 1, including similar content from previous researches.

Regarding the benefits, this research examined two types of subjective rank expressions: comparison and degree [4], where the former describes the results of comparisons with other benefits and the latter directly describes the rank of benefits using adjectives and adverbs. A typical example of the comparison type is a message like "The touch panel LCD of product X is easier to use than that of product Y," which claims that this attribute of X is rated higher than that of Y with respect to the benefit; easy to use. On the other hand, a typical example of the degree type is a message like "The touch panel LCD of product X is incredibly easy to use," which claims the attribute of X is rated high with respect to the benefit. Since both messages are concerned with the attitude-levels of product attributes for a benefit, they involve subjective rank expressions. As shown in the example messages, eWOM messages involving subjective rank expressions contain not only information connecting attributes to benefits but also information related to the authors' attitude-levels of the benefits of attributes.

The "potency" of eWOM messages in this paper relates to the attitude change in the product evaluations when the receiver is exposed to the message. Message m_1 has larger potency than m_2 when the degree of the attitude change by m_1 is larger than m_2. The potency depends not only on the message content but also on the characteristics of the message receivers and of the evaluated products, so a different person as well as a different product may give different potency with respect to the same message content [20]. There are two types of potency: positive and negative. The former changes the product evaluations

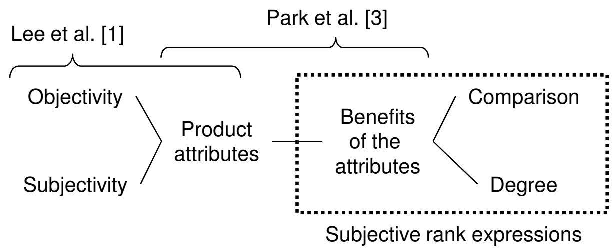


Figure 1. Subjective rank expressions and related work.

positively and the latter changes them negatively [21], [22]. This paper focuses on positive potency because one aim of this research is to develop intelligent agents that selectively provide eWOM messages to increase consumer purchase intention.

Some psychological measurements of attitude change are often used to determine the potency of eWOM messages (e.g., [1], [3]). Such measurements are also used in the area of persuasion research [8], [23], which is closely related to advertising and word-of-mouth researches. In persuasion researches, the term "persuasiveness" is often used instead of potency. The difference between persuasiveness and potency is the presence or absence of a goal and the intention to reach the goal of the message providers; i.e., the term persuasiveness postulates such a goal but the term potency does not.

B. Cognitive Hypotheses

The cognitive hypotheses proposed in [4] focus attention on how much inference is required for the message receiver to know the author's attitude-level of the targets through the message. Since consumers with high expertise in the products are likely to infer based on their own knowledge, they are expected to prefer comparison type in which the attitude-level is not written explictly and leaves room for personal determinations. In contrast, since consumers with low expertise are likely to dislike such inferences, they are expected to prefer the degree type in which the attitude-level has already been determined by the author so that the evaluation can be directly obtained by the message. Thus, the following hypotheses were proposed [4].

Hypothesis A: For consumers with high expertise, comparison type eWOM messages for targets has larger potency on the evaluation of the targets than degree type eWOM.

Hypothesis B: For consumers with low expertise, degree type eWOM messages for targets has larger potency on the evaluation of the targets than comparison type eWOM.

These hypotheses were supported by hypothesis testing on the dataset collected from a questionnaire survey administered to one hundred and fifty two undergraduate students [4].

A theoretical background of the hypotheses is the theory of *implicit conclusions* [24]–[26], which was developed mainly to account for the persuasiveness of advertising. For example, a typical ad with an explicit conclusion is "Now That You Know the Difference, Shave With Edge – The Disposable Razor That is Best for You." A typical one with an implicit conclusion is "Now That You Have the Facts, Decide for Yourself Which Toothbrush You Should Buy," as introduced in [24]. It states that ads with implicit conclusions are expected to be persuasive when the audience is highly involved in the products instead of being lowly involved. Sawyer et al. explained the persuasiveness as follows [25]: "Perhaps the most important reason is that the absence of any obvious conclusion may lead a motivated audience to try to infer one. $\cdots$ Attitudes resulting from effortful self-generated conclusions should be more positive than attitudes resulting from less effortful processing of conclusions explicitly provided in a message and more accessible and persistent over time." The theory of implicit conclusions was empirically supported [25], [26] and extended from wider viewpoints such as attention for visual material [27] and missing attributes [28].

The cognitive hypotheses [4] can be viewed as one application of the theory of implicit conclusions and, in that sense, are characterized from two aspects. First, the hypotheses focus on the inference of the author's attitude-levels toward targets through messages and regard the attitude-levels as "conclusions." Second, the hypotheses incorporate the expertise of message receivers instead of their involvement, which is a motivational parameter used by the message receiver to infer the conclusions. As Chebat et al. suggested, both expertise and involvement should be considered to obtain accurate potency predictions [29]. However, this paper only considers expertise because it is not so difficult to extend the idea with expertise only to the one with both factors by assuming no interaction effect between them.

Expertise of products has various aspects, or dimensions [18], and is measured in various ways. For example, Park et al. used the number of correct responses to questions about the products and performed a median-split technique to divide consumers into experts and novices [3]. As another example, the author defined expertise with respect to having/not having an experience of purchasing products, where expert and novice refer to having and not having [4]. At a more practical setting for intelligent agents, expertise may be determined with keywords or bookmarks used or possessed by users.

C. Research Purpose

Previous work [4] focused on two message types: comparison and degree; but subjective rank expressions should have a wide variety of message subtypes. For example, gradable comparatives are classified into three subtypes: non-equal gradable, equative, and superlative [30]. The similarity or difference between two objects may generate other subtypes, as shown in [31]. In addition, there may be messages in which two or more types are combined. Such a wide variety of message types requires the cognitive hypotheses to be very generalized. The purpose of the current research is to achieve generalization by developing a computational model that measures the amount of required inference (Q) for such various messages. The generalized hypothesis becomes the following: for any two eWOM messages m_i and m_j, if $Q(m_i) > Q(m_j)$ then m_i has larger potency than m_j for experts and, conversely, m_j has larger potency than m_i for novices.

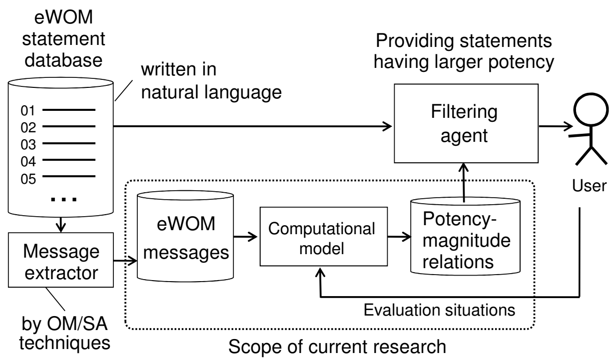


Figure 2. Illustrative application of computational model.

Fig. 2 shows an illustrative application of the computational model and the scope of this research. In the figure, the filtering agent selects the eWOM statements based on the potency-magnitude relations generated from the computational model, which is the main topic of this paper. To obtain the potency-magnitude relations on the eWOM statements written in natural language, the message extractor constructed by opinion mining and sentiment analysis (OM/SA) techniques extracts subjective messages, which are the eWOM messages in the figure, as definite shapes from the natural language statements. Then the computational model generates the potency-magnitude relations on the messages based on the evaluation situations of the user. Although both positive and negative eWOM statements exist when they are gathered through social media, only positively evaluated messages for products are selected and used to promote the purchase intention of system users. As shown in the figure, the scope of this research does not directly include the techniques in the area of OM/SA. However, OM/SA research is closely related to my current research because the formats of the messages should be determined based on the techniques.

III. MESSAGE MODELING

A. Comparison Type

Two of the most fundamental categories for human opinion are comparative and direct [6]. A direct opinion expresses a subjective idea on a single object, while a comparative opinion expresses a relation of differences or similarities between two or more objects and/or object preferences of the opinion holder. Comparatives are classified into four subtypes: non-equal gradable, equative, superlative, and non-gradable [30].

Based on the subtypes of the comparatives, the eWOM messages in the comparison type of the subjective rank expressions are modeled as follows:

(*target1, target2, type*),

where *target1* and *target2* are the sets of the pairs of a benefit and a product attribute and *type* is one of the three subtypes: non-equal gradable, equative, and superlative. For the non-equal gradable (equative) *type*, the messages insist that the attitude-levels of *target1* are larger than (are equal to) those of *target2*. For the superlative *type*, the messages insist that the attitude-levels of *target1* are the largest among all other targets to be evaluated; *target2* is omitted. The parameter *type* excludes non-gradable from its values because non-gradable does not address the attitude-levels of targets.

The message model proposed here may be obtained by adjusting Jindal's message model using five parameters: *relationWord*, *features*, *entityS1*, *entityS2*, and *type* [30]. Parameters *features*, *entityS1*, and *entityS2* are related to *target1* and *target2* in the proposed model, while parameter *type* is the same in both models. Parameter *relationWord* takes a keyword such as *-er* or *exceed* that is used to express a comparative relation in a sentence. Although the proposed model does not contain parameter *relationWord*, the benefits in *target1* and *target2* may contain a piece of the parameter information when it has beneficial words such as easier and lightest.

Note that, although the message model proposed here is similar to the Jindal's model in the appearance, they are different in the semantics of the comparison. That is, the message model proposed here compares the attitude-levels of targets whereas the Jindal's model compares certain features like length and size of entities. Therefore, they may generate different structures of the comparative relations. For example, for digital cameras, a message like "The start up time of X is longer than that of Y." constructs the relation X $>$ Y with respect to the length of time by the Jindal's model whereas it constructs the relation X $<$ Y with respect to the attitude-levels by the proposed model (Shorter is better in this case.). The issue described here is also discussed in [32], [33].

B. Degree Type

One typical problem in the research area is polarity detection that classifies an online review as positive or negative at a document level [34] or a sentence level [35]. Recently, the rating-inference problem is also studied to classify not into two classes, positive or negative, but into fine-grained rating classes (e.g., one to five "stars") [36]. Rating-inference tasks determine an author's evaluation from the review texts with respect to a multi-point rating scale, which is a kind of ordinal scale. The latent message models that the tasks postulate appear to have three elements: an evaluated object, its rated level, and a multi-point rating scale for the evaluation.

Based on this idea, the eWOM messages in the degree type of subjective rank expressions are modeled as follows:

(*target, level, scaleInfo*),

where *target* is a set of the pairs of a benefit and a product attribute and *level* is the attitude-level based on *scaleInfo*, which is the specifications of the multi-point rating scale used. The specifications include the number of points on the rating scale and, if required, the polarity that each point belongs. Five-point Likert type scales, which are often used in psychological experiments, are one alternative for the rating scales. In the case, the number of points on the rating scales is five and points 1, 2 belong negative, 3 belongs neutral, and 4, 5 belong positive attitude.

The granularity of the multi-point rating scale has variations. Pang et al. discussed a reasonable classification granularity to determine other persons' evaluations by using Internet movie reviews [36]. They examined pairs of reviews extracted from the review set to determine whether the first review in each pair was more positive than, less positive than, or as positive as the second. They concluded that the reasonable scale size, which is the number of points on the rating scale, is not so large and is four or five. As they discussed, much finer-grained may not be reasonable when no information exists to discern such finer-grained levels in the message texts. There may not be enough text samples to create classification rules with finer-grained scales using machine learning techniques. The granularity of the multi-point rating scale is determined practically by considering such properties of the message texts.

IV. Computational Model

A. Basic Idea

In the computational model, the amount of required inference is quantified as the *inference quantum*. Messages explicitly containing an attitude-level enable it to be obtained directly, and thus they require no inference; the size of inference quantum is 0. Since messages containing only comparative relations of the attitude-levels require some inference to obtain the levels, the inference quantum is not 0 but has a certain value. The inference quantum does not postulate the levels contained in a single message but postulates the set of the levels of all targets to be evaluated. Therefore, the computational model incorporates the idea of *inference space* that contains all possible attitude-levels inferred by the message receiver.

The dimensions of the inference space correspond to the targets to be evaluated. Fig. 3 shows an example of the inference space where two targets, A and B, are evaluated and a 5-point rating scale ranging from 1 to 5 is used to evaluate the attitude-levels. The horizontal and vertical axes represent the attitude-levels of A and B, which are denoted as h(A) and h(B), respectively. The inference space consists of 25 points in this case. A certain point in the inference space gives the attitude-levels of all targets, A and B. For example, point $e = (4, 3)$ indicates that the attitude-levels of targets A and B are 4 and 3, respectively.

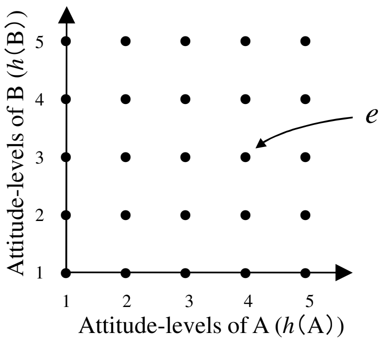


Figure 3. Inference space.

Thus, based on inference space, the determination tasks of the attitude-levels of the targets are regarded as the determination of one point in the inference space. The idea of inference space was inspired in part by distribution hyperspace [37] and its extension [38].

The inference quantum of messages giving stronger constraints in the inference space is considered smaller because such messages limit the inferred space to a narrower region. On the other hand, the inference quantum of messages giving weaker constraints is considered larger because such messages allow the inferred space to be wider. Thus, the inference quantum is expected to be quantified using the size of the compatible regions in the inference space with the message.

B. Formalization

As notations for inference space, the following symbols are used.

- Target set Ω denotes the set of all targets to be evaluated. Evaluation target size k, which is a finite integer greater than or equal to 1, denotes the size of Ω.
- Evaluation scale size ν, which is a finite integer greater than or equal to 2, denotes the number of points on the rating scale used for the attitude-level evaluations. It is also written like ν point rating scales.
- A pair of k and ν, denoted $\lambda = (k, \nu)$, is called evaluation parameters.
- Inference space $\Theta_\lambda = \{e_1, \ldots, e_{\nu^k}\}$ denotes the set of all possible attitude-levels for all k targets by using the ν point rating scale. The elements e_j, $j = 1, \ldots, \nu^k$ are called points in Θ_λ.

Next consider a set of messages $M = \{m_1, \ldots, m_n\}$, each of which is eWOM message involving subjective rank expressions for one or more targets in Ω. The points of Θ_λ compatible with $m_i \in M$ are denoted as r_i. Based on the idea of inference space Θ_λ and compatible points r_i of Θ_λ, the inference quantum is defined below.

Definition (Inference Quantum)

The *inference quantum* Q of a message $m_i \in M$ for a message receiver with evaluation parameters λ is defined by

$$Q(m_i) = \log_2 \sum_{e \in \Theta_\lambda} \eta_i(e) \ , \qquad (1)$$

where η_i is a function:

$$\eta_i(e) = \begin{cases} 1 & \text{if } e \in r_i \\ 0 & \text{if } e \notin r_i \end{cases} . \qquad (2)$$

The inference quantum Q takes an integer ranging from 0 to $k \log \nu$. Maximum value $k \log \nu$ of the inference quantum is given to the messages that are compatible with all of the inference space, but minimum value 0 is given to the messages that have only one compatible point in the inference space. The inference quantum is denoted by Q_λ when the evaluation parameters should be written explicitly.

Based on the inference quantum, the computational rule for predicting potency-magnitude relations between two eWOM messages is described below.

Prediction Rule

If $Q(m_i) > Q(m_j)$, both m_i and $m_j \in M$ give positive support to a target $\in \Omega$,
then $m_i \succ m_j$ for experts and
$m_j \succ m_i$ for novices,
where $m_i \succ m_j$ ($m_j \succ m_i$) denotes m_i (m_j) is expected to have larger potency than m_j (m_i) with respect to the positive attitude change in the target.

As shown in the prediction rule, potency-magnitude relations are derived by discerning the expertise level of the message receiver of the products. Note that the rating scale for an inference space is determined based on the cognitive perspective of the message receiver's evaluations. Therefore, it may not be compatible with the rating scales for degree type messages because the scales are often determined previously with some practical conditions in the message extraction techniques. However, the identical scale should be used because when a different scale is used, a mapping rule between the scales has to be developed to obtain compatible region r_i with the messages. To conform the scale for the degree type messages to the scale for the inference space, it is necessary to previously prepare degree type messages not in a single type rating scale but in several types and to choose messages in a compatible type when the inference space is determined.

C. Example

This subsection illustrates the prediction processes using two different situations of evaluation parameters, λ_a and λ_b, as shown in Table I(a). The target set on λ_a consists of A, B, and C, that is, $k = 3$, whereas that on λ_b consists of A, B, C, and D, that is, $k = 4$. The evaluation scale size ν on λ_a and λ_b is the same value, 5. The inference space for λ_a contains 125 ($= 5^3$) points,

TABLE I.
PARAMETERS AND MESSAGES IN ILLUSTRATIVE EXAMPLE

(a) Evaluation parameters

	Target set Ω	Size of Ω	Scale size
λ_a	A, B, C	$k = 3$	$\nu = 5$
λ_b	A, B, C, D	$k = 4$	

(b) eWOM messages

	Representations	Compatible Region
m_1	(A, B, non-equal gradable)	$h(A) > h(B)$
m_2	(A, , superlative)	$h(A) > h(*)$
m_2	(A, 5, {5-point scale, 1 to 5})	$h(A) = 5$

"*" indicates any other target in Ω.

TABLE II.
COMPUTATIONAL RESULTS

(a) Inference quantum $Q(m_i)$ for each message

	m_1	m_2	m_3
λ_a	5.64	4.91	4.64
λ_b	7.97	6.64	6.97

(b) Potency-magnitude relations among messages

	Experts	Novices
λ_a	$m_1 \succ m_2 \succ m_3$	$m_3 \succ m_2 \succ m_1$
λ_b	$m_1 \succ m_3 \succ m_2$	$m_2 \succ m_3 \succ m_1$

so the inference quantum based on λ_a ranges from 0 to $3 \log 5$ (=6.97). On the other hand, the inference space for λ_b contains 625 ($= 5^4$) points, so the inference quantum based on λ_b ranges from 0 to $4 \log 5$ (=9.29).

The eWOM messages used in this illustration are shown in Table I(b). Message m_1 is the non-equal gradable type and means that the attitude-level of A is larger than that of B. It specifies the region where h(A) $>$ h(B) in the inference space. Message m_2 is the superlative type and means that the attitude-level of A is the largest. It specifies the intersectional region of "h(A) $>$ h(B)" and "h(A) $>$ h(C)" for λ_a and the intersectional region of "h(A) $>$ h(B)," "h(A) $>$ h(C)," and "h(A) $>$ h(D)" for λ_b. Message m_3 is the degree type and means that the attitude-level of A is 5 on the 5-point rating scale ranging from 1 to 5. It specifies the region where h(A) = 5 in the inference space. All these messages positively support target A, so that the prediction rule derives the potency-magnitude relations with respect to the positive attitude change in target A.

Table II(a) shows the calculation results of the inference quantum of the eWOM messages. For λ_a, the inference quanta of m_1, m_2, and m_3 are 5.64, 4.91, and 4.64, respectively. For λ_b, the inference quanta of m_1, m_2, and m_3 are 7.97, 6.64, and 6.97, respectively. Table II(b) shows the potency-magnitude relations derived from the prediction rule. With respect to λ_a, relations $m_1 \succ m_2 \succ m_3$ for experts and relations $m_3 \succ m_2 \succ m_1$ for novices are obtained. This suggests that a promising strategy of intelligent filtering agents to promote A is achieved by giving priority to m_1 for experts and to m_3 for novices. On the other hand, with respect to λ_b, relations $m_1 \succ m_3 \succ m_2$ for experts and relations $m_2 \succ m_3 \succ m_1$ for novices are obtained. This suggests that a promising strategy of intelligent filtering agents to promote A is achieved by giving priority to m_1 for experts and to m_2 for novices.

Note that a reversal phenomenon of the potency-magnitude relations between m_2 and m_3 was observed in the computational results, i.e., the relation $m_2 \succ m_3$ ($m_3 \succ m_2$) in λ_a is reversed as $m_3 \succ m_2$ ($m_2 \succ m_3$) in λ_b for experts (for novices). This observation suggests that the message receiver's situation of evaluation parameters may change the potency-magnitude relations. In other words, accurate prediction of the potency-magnitude relations can not be achieved without considering the values of evaluation parameters where the message receiver evaluates products with eWOM messages.

V. MATHEMATICAL PROPERTIES

This section defines three message-classes and mathematically investigates how the potency-magnitude relations change based on the values of evaluation parameters k and ν. The mathematical investigations construct *Q-magnitude Relation Map (Q-Map)*, which (1) partitions the space spanned by k and ν into disjoint regions such that different regions give different magnitude-relations of inference quanta and (2) labels the regions to give the same label for the regions where the same magnitude-relation holds. This section also derives *Priority Message-Class Map (P-Map)* for experts and novices by applying the prediction rule to the Q-Map. The P-Map contributes to develop eWOM message filtering strategies. The assumptions used in this section are summarized below:

- The prediction rule is applied to an evaluation situation where a message receiver evaluates products with eWOM messages. Therefore, to derive the magnitude relations of the inference quanta, they are compared on the same evaluation parameter values. This means that when we say $Q(m_i) > Q(m_j)$, terms $Q(m_i)$ and $Q(m_j)$ are calculated by the same k and by the same ν.
- Each receiver has target set Ω and uses messages for the targets in Ω to make decisions. Therefore, all targets in all the messages to be compared are contained in target set Ω. This means that the evaluation target size k is larger than or equal to 2 on the premise of the non-equal gradable type, which contains two different targets at least.

A. Calculating Formula of Inference Quantum

Messages m_1, m_2 and m_3 used in the Section IV example are generalized by using message-classes $M^{(1,1)}_{type1}, M^{(1)}_{type2}$, and $M^{(1)}_{type3}$, respectively:

$M^{(1,1)}_{type1}$: The set of all non-equal gradable type messages that insist the attitude-level of a target ($\in \Omega$) is larger than that of another target ($\in \Omega$).

$M^{(1)}_{type2}$: The set of all superlative type messages that insist the attitude-level of a target ($\in \Omega$) is larger than those of all other targets ($\in \Omega$).

$M^{(1)}_{type3}$: The set of all degree type messages that insist the attitude-level of a target ($\in \Omega$) is a certain value on a ν point rating scale.

As shown in these definitions, the message-classes neither depend on the target names nor on particular attitude-levels in the degree type messages. This section does not use m_1, m_2, and m_3 directly, but instead uses messages $m^{(1,1)}_{type1}, m^{(1)}_{type2}$, and $m^{(1)}_{type3}$, each of which belongs to classes $M^{(1,1)}_{type1}, M^{(1)}_{type2}$, and $M^{(1)}_{type3}$, respectively. For example, the statement "$Q(m^{(1,1)}_{type1}) > Q(m^{(1)}_{type2})$" is used to state "$Q(m_i) > Q(m_j)$ for all $m_i \in M^{(1,1)}_{type1}, m_j \in M^{(1)}_{type2}$."

The inference quanta of $m^{(1,1)}_{type1}$, $m^{(1)}_{type2}$, and $m^{(1)}_{type3}$ are calculated from evaluation parameters k and ν as the following formulae:

$$Q(m^{(1,1)}_{type1}) = \log \frac{\nu^{k-1}(\nu-1)}{2}. \quad (3)$$

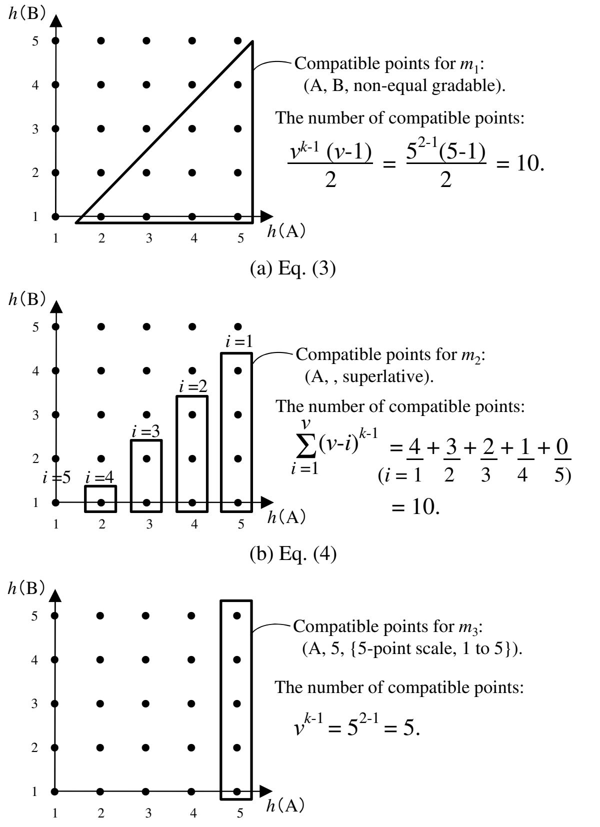
$$Q(m^{(1)}_{type2}) = \log \left(\sum_{i=1}^{\nu} (\nu - i)^{k-1} \right). \quad (4)$$

$$Q(m^{(1)}_{type3}) = \log \nu^{k-1}. \quad (5)$$

The explanations for them are described below:

- Eq. (3): The number of compatible points with message $m^{(1,1)}_{type1}$ in the inference space's subspace spanned by the two targets described in the message becomes $(\nu^2 - \nu)/2$ because it excludes the points where two targets have the same attitude-level and the points where a target has smaller attitude-levels than another target. It is multiplied by ν^{k-2} to consider other dimensions that correspond to other targets in Ω. Then $\nu^{k-1}(\nu-1)/2$ is obtained.
- Eq. (4): When the attitude-level of the target described in the message takes largest value ν ($i = 1$), the number of compatible points with message $m^{(1)}_{type2}$ in the inference space becomes $(\nu-1)^{k-1}$ because the attitude-levels of other targets in Ω can take any level less than or equal to $(\nu - 1)$. In the same way, when the attitude-level of the target described in the message takes value $\nu - 1$ ($i = 2$), the number of compatible points in the inference space becomes $(\nu - 2)^{k-1}$. Considering from $i = 1$ to ν, $\sum_{i=1}^{\nu}(\nu - i)^{k-1}$ is obtained.
- Eq. (5): The number of compatible points with message $m^{(1)}_{type3}$ in the inference space's subspace spanned by the target described in the message becomes 1 because it specifies a single point in the subspace. In the same way for message $m^{(1,1)}_{type1}$, it is multiplied by ν^{k-1} to consider other dimensions that correspond to other targets in Ω. Then ν^{k-1} is obtained.

Example Simple numerical examples where $k = 2$ and $\nu = 5$ are presented to illustrate the idea of Eqs. (3)-(5). Three messages m_1, m_2, and m_3 introduced in the previous section (Table I(b)) are used to show the number of compatible points visually.



(a) Eq. (3)
(b) Eq. (4)
(c) Eq. (5)

Figure 4. Illustrative examples ($k = 2, \nu = 5$) for Eq. (3), (4) and (5).

(a) From Eq. (3), $Q(m^{(1,1)}_{type1}) = \log \frac{5^{2-1}(5-1)}{2} = \log 10$ is obtained. Fig. 4(a) illustrates the number of compatible points for $m_1 \in M^{(1,1)}_{type1}$.

(b) From Eq. (4), $Q(m^{(1)}_{type2}) = \log \left(\sum_{i=1}^{5}(5-i)^{2-1} \right) = \log 10$ is obtained. Fig. 4(b) illustrates the number of compatible points for $m_2 \in M^{(1)}_{type2}$.

(c) From Eq. (5), $Q(m^{(1)}_{type3}) = \log 5^{2-1} = \log 5$ is obtained. Fig. 4(c) illustrates the number of compatible points for $m_3 \in M^{(1)}_{type3}$.

Some propositions shown in the next section are proved not by using inference quantum Q directly but using function E, which is defined without the logarithm function in Eq. (1); that is, $Q(\cdot) = \log_2 E(\cdot)$. The usage of E works with Lemma shown below.

Lemma
(a) Suppose two messages, m_i and m_j ($\in M$). If $E(m_i) > E(m_j)$ then $Q(m_i) > Q(m_j)$.
(b) Suppose two messages, m_i and m_j ($\in M$), such that $E(m_j) \neq 0$. If $E(m_i)/E(m_j) > 1$ then $Q(m_i) > Q(m_j)$.

Proof: (a) $E(m_i) > E(m_j) \Rightarrow \log E(m_i) > \log E(m_j)$.
(b) $E(m_i)/E(m_j) > 1 \Rightarrow \log\{E(m_i)/E(m_j)\} > \log 1 \Rightarrow \log E(m_i) - \log E(m_j) > 0$. □

B. Mathematical Propositions

Three mathematical propositions for the magnitude relations of the inference quanta between $m^{(1,1)}_{type1}$ and $m^{(1)}_{type2}$, between $m^{(1,1)}_{type1}$ and $m^{(1)}_{type3}$, and between $m^{(1)}_{type2}$ and $m^{(1)}_{type3}$ are presented as follows:

Proposition 1 *(Between $m^{(1,1)}_{type1}$ and $m^{(1)}_{type2}$)*
(a) When $k = 2$ and $\nu \geq 2$, $Q(m^{(1,1)}_{type1}) = Q(m^{(1)}_{type2})$.
(b) When $k \geq 3$ and $\nu \geq 2$, $Q(m^{(1,1)}_{type1}) > Q(m^{(1)}_{type2})$.

Proof: (a) By substituting $k = 2$ for Eqs. (3) and (4), it is easy to confirm $Q(m^{(1,1)}_{type1}) = Q(m^{(1)}_{type2})$ for all $\nu \geq 2$. (b) (i) By substituting $\nu = 2$ for Eqs. (3) and (4), it is easy to confirm $E(m^{(1,1)}_{type1}) > E(m^{(1)}_{type2})$ for all $k \geq 3$. (ii) When ν becomes $\nu + 1$, the amount of change $\Delta E(m^{(1,1)}_{type1}) > \Delta E(m^{(1)}_{type2})$ for all $k \geq 3$. Thus, by using Lemma (a), $Q(m^{(1,1)}_{type1}) > Q(m^{(1)}_{type2})$ for all $k \geq 3$ and $\nu \geq 2$ follows from the principle of mathematical induction. □

Proposition 2 *(Between $m^{(1,1)}_{type1}$ and $m^{(1)}_{type3}$)*
(a) When $k \geq 2$ and $\nu = 2$, $Q(m^{(1,1)}_{type1}) < Q(m^{(1)}_{type3})$.
(b) When $k \geq 2$ and $\nu = 3$, $Q(m^{(1,1)}_{type1}) = Q(m^{(1)}_{type3})$.
(c) When $k \geq 2$ and $\nu \geq 4$, $Q(m^{(1,1)}_{type1}) > Q(m^{(1)}_{type3})$.

Proof: (a) By substituting $\nu = 2$ for Eqs. (3) and (5), it is easy to confirm $Q(m^{(1,1)}_{type1}) < Q(m^{(1)}_{type3})$ for all $k \geq 2$. (b) By substituting $\nu = 3$ for Eqs. (3) and (5), it is easy to confirm $Q(m^{(1,1)}_{type1}) = Q(m^{(1)}_{type3})$ for all $k \geq 2$. (c) $E(m^{(1)}_{type3}) \neq 0$ allows us to consider ratio $E(m^{(1,1)}_{type1})/E(m^{(1)}_{type3})$. It is easy to confirm that the ratio is greater than 1 for all $k \geq 2,\ \nu \geq 4$. Thus, the statement follows from Lemma (b). □

Proposition 3 *(Between $m^{(1)}_{type2}$ and $m^{(1)}_{type3}$)*
(a) When $k \geq 2$ and $\nu = 2$, $Q(m^{(1)}_{type2}) < Q(m^{(1)}_{type3})$.
(b) For all $k \geq 2$, there exists $\nu \geq 2$ such that $Q(m^{(1)}_{type2}) > Q(m^{(1)}_{type3})$.
(c) For all $k \geq 2$ and $\nu \geq 2$, $Q(m^{(1)}_{type2}) - Q(m^{(1)}_{type3})$ monotonically increases in ν.

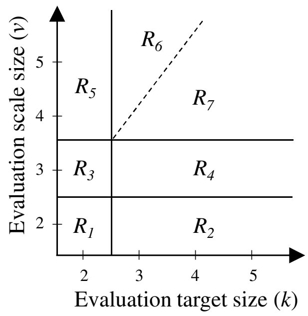
Proof: (a) By substituting $\nu = 2$ for Eqs. (4) and (5), it is easy to confirm $Q(m^{(1)}_{type2}) < Q(m^{(1)}_{type3})$ for all $k \geq 2$. (b) $E(m^{(1)}_{type3}) \neq 0$ allows us to consider ratio $E(m^{(1)}_{type2})/E(m^{(1)}_{type3})$ ($\equiv I_\nu$). We can write ratio I_ν as $(\frac{\nu-1}{\nu})^{k-1} + (\frac{\nu-2}{\nu})^{k-1} + \cdots + (\frac{1}{\nu})^{k-1}$. It is enough to show that the sum of the first two terms of the ratio is larger than 1 because none of the terms of the ratio take negative values. The ratio's first two terms, which are $(\frac{\nu-1}{\nu})^{k-1}$ and $(\frac{\nu-2}{\nu})^{k-1}$, both monotonically increase in ν and become 1 when $\nu \to \infty$ (They do not become 1 because ν is finite, but tend to 1 monotonically as g increases without limit.). This holds for all $k \geq 2$. Therefore, by taking a sufficiently large ν, we can find ν such that $E(m^{(1)}_{type2})/E(m^{(1)}_{type3}) > 1$ for all $k \geq 2$. Thus, the statement follows from Lemma (b). (c) In the same way as (b), I_ν is used. When ν becomes $\nu + 1$, the ratio ($I_{\nu+1}$) becomes $(\frac{\nu}{\nu+1})^{k-1} + (\frac{\nu-1}{\nu+1})^{k-1} + \cdots + (\frac{1}{\nu+1})^{k-1}$. The difference $I_{\nu+1} - I_\nu$ is larger than 0 for all $k \geq 2$ and $\nu \geq 2$ because $I_{\nu+1} - I_\nu = \sum_{i=1}^{\nu}\{\frac{(\nu+1-i)^{k-1}}{(\nu+1)^{k-1}} - \frac{(\nu-i)^{k-1}}{\nu^{k-1}}\}$, where $\frac{(\nu+1-i)^{k-1}}{(\nu+1)^{k-1}} > \frac{(\nu-i)^{k-1}}{\nu^{k-1}}$ for all $k \geq 2$ and $\nu \geq 2$. Thus, $Q_{\nu+1}(m^{(1)}_{type2}) - Q_{\nu+1}(m^{(1)}_{type3})$ is larger than $Q_\nu(m^{(1)}_{type2}) - Q_\nu(m^{(1)}_{type3})$ for all $k \geq 2$ and $\nu \geq 2$ follows from Lemma (b). □

C. Q-magnitude Relation Map (Q-Map)

The three propositions construct a Q-Map for $m^{(1,1)}_{type1}$, $m^{(1)}_{type2}$, and $m^{(1)}_{type3}$. Fig. 5 shows the Q-Map, which consists of seven disjoint regions: $R_1, R_2, \ldots, R_7$.

Regions $R_1, R_2, \ldots, R_5$ are determined by Propositions 1 and 2. For example, Propositions 1(a) and 2(a) specify the magnitude relation of the inference quantum for R_1 ($k = 2, \nu = 2$) as $Q(m^{(1,1)}_{type1}) = Q(m^{(1)}_{type2}) < Q(m^{(1)}_{type3})$. For another example, Propositions 1(b) and 2(b) specify the magnitude relation of the inference quantum for R_4 ($k \geq 3, \nu = 3$) as $Q(m^{(1)}_{type2}) < Q(m^{(1,1)}_{type1}) = Q(m^{(1)}_{type3})$.

On the other hand, regions R_6 and R_7 are developed with Proposition 3. In summary, Proposition 3 describes the reversal phenomenon of the magnitude relation between $Q(m^{(1)}_{type2})$ and $Q(m^{(1)}_{type3})$. Specifically, Propositions 3(a) and (b) state that $Q(m^{(1)}_{type2})$ is smaller than $Q(m^{(1)}_{type3})$ when ν is small ($\nu = 2$), but there exists ν such that $Q(m^{(1)}_{type2})$ is larger than $Q(m^{(1)}_{type3})$ when ν becomes large. In addition, Proposition 3(c) states that if once $Q(m^{(1)}_{type2})$ becomes larger than $Q(m^{(1)}_{type3})$ by increasing ν, then $Q(m^{(1)}_{type2})$ never becomes smaller than $Q(m^{(1)}_{type3})$ by additional increases of ν. This allows us to

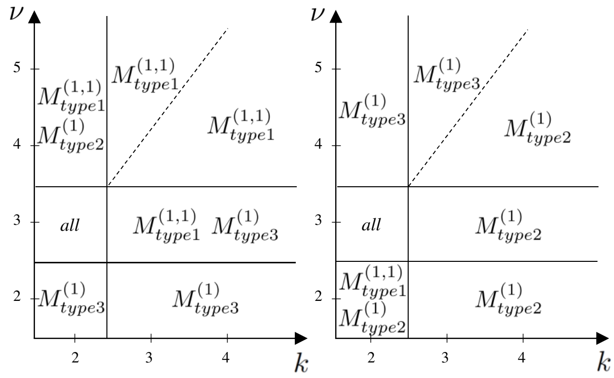


R_1 : $Q(m^{(1,1)}_{type1}) = Q(m^{(1)}_{type2}) < Q(m^{(1)}_{type3})$
R_2 : $Q(m^{(1)}_{type2}) < Q(m^{(1,1)}_{type1}) < Q(m^{(1)}_{type3})$
R_3 : $Q(m^{(1,1)}_{type1}) = Q(m^{(1)}_{type2}) = Q(m^{(1)}_{type3})$
R_4 : $Q(m^{(1)}_{type2}) < Q(m^{(1,1)}_{type1}) = Q(m^{(1)}_{type3})$
R_5 : $Q(m^{(1,1)}_{type1}) = Q(m^{(1)}_{type2}) > Q(m^{(1)}_{type3})$
R_6 : $Q(m^{(1,1)}_{type1}) > Q(m^{(1)}_{type2}) > Q(m^{(1)}_{type3})$
R_7 : $Q(m^{(1,1)}_{type1}) > Q(m^{(1)}_{type3}) > Q(m^{(1)}_{type2})$

Figure 5. Q-magnitude relation map (Q-Map).

divide the region where $k \geq 3$ and $\nu \geq 4$ into two: R_6 and R_7. Note that the boundary between R_6 and R_7 (dash-line in the figure) may have another region where $Q(m^{(1)}_{type2})$ equals $Q(m^{(1)}_{type3})$. This indeterminacy disappears if it can be proven that there is no integer $k \geq 2$ and $\nu \geq 2$, except for $k = 2$ and $\nu = 3$, such that $Q(m^{(1)}_{type2}) = Q(m^{(1)}_{type3})$. At this time, it is only confirmed by computer simulation techniques that the condition holds for all $2 \leq k \leq 100$ and $2 \leq \nu \leq 100$.

Thus, the magnitude relations of the inference quanta of the three messages consist of seven patterns, each of which is determined by the region in the evaluation parameter space.



(a) experts (b) novices

Figure 6. Priority message-class map (P-Map).

D. Priority Message-class Map (P-Map)

The P-Map for $M^{(1,1)}_{type1}$, $M^{(1)}_{type2}$, and $M^{(1)}_{type3}$ is obtained by applying the prediction rule to the Q-Map with respect to positive attitude changes in a target ($\in \Omega$). Only messages that give positive support to the target are considered when the prediction rule is applied. Figs. 6(a) and (b) show the P-Map for experts and novices, each of which consists of seven disjoint regions, the same as the Q-Map.

The message-classes indicated in each region of the P-Map are the expected classes with the largest potency with respect to the prediction rule. For example, region $k = \nu = 2$ of the P-Map for experts indicates $M^{(1)}_{type3}$. This means, for experts, the potency of $m^{(1)}_{type3}$ exceeds that of $m^{(1,1)}_{type1}$ and of $m^{(1)}_{type2}$. In the same way, the regions indicating two message-classes mean that their potency is the same and larger than the potency of messages in the other class. The regions indicating "*all*," where $k = 2$ and $\nu = 3$ for experts and novices, mean that the potency of messages in the three message-classes is the same.

P-Maps guarantee that no message has larger potency than messages in the message-classes indicated in the region. Thus, it is a rational filtering strategy that gives priority to provide the messages belonging to the message-classes shown in the P-Map's region to which the evaluation parameter belongs. For example, for experts on $k \geq 3$ and $\nu = 2$, message $m^{(1)}_{type3}$ is given priority to provide, in contrast, for experts on $k = 2$ and $\nu \geq 4$, messages $m^{(1,1)}_{type1}$ and $m^{(1)}_{type2}$ are given priority. In the same way, for novices on $k \geq 3$ and $\nu = 2$, message $m^{(1)}_{type2}$ is given priority to provide, in contrast, for novices on $k = 2$ and $\nu \geq 4$, message $m^{(1)}_{type3}$ is given priority.

As illustrated here, message filtering strategies based on P-Maps postulate the values of evaluation parameters, represented by k and ν, where the users evaluate products with eWOM messages. It may be difficult to know previously the values because they depend not only on the type and the number of products evaluated by the user but also on the rating scale used by the user. Fortunately, the P-Map shown in Fig. 6 suggests that there are cases in which the exact values of the evaluation parameters don't have to be known. For example, for experts, not depending on k, message $m^{(1,1)}_{type1}$ always belongs to the priority message-classes when $\nu \geq 3$, and message $m^{(1)}_{type3}$ always belongs to the priority message-classes when $\nu \leq 3$. This suggests that we do not have to know k when ν can be estimated. Such analytical investigations will contribute to reduce the preciseness requirements for k and ν estimation.

VI. Conclusion and Future Work

This paper presented a computational model that predicts the potency-magnitude relations of eWOM messages involving subjective rank expressions. This paper defined three message-classes and investigated mathematically how the potency-magnitude relations change based on the values of two evaluation parameters: evaluation target size k and evaluation scale size ν.

The mathematical investigations developed a Q-magnitude Relation Map (Q-Map) and a Priority Message-class Map (P-Map), which are exploited to design eWOM message filtering strategies. Message filtering strategies based on P-Maps postulate the values of evaluation parameters. This paper discussed that some analytical investigations reduce the preciseness requirements for the parameter estimations (Section V. D.). Future work includes further investigations and finding some observable factors for the estimation.

The observable factors for evaluation target size k may be related to the products evaluated by the user. A complex product with various specifications (e.g., digital cameras) will provide larger k than a simple product (e.g., a PC mouse). In addition, the increase of the number of product alternatives to be chosen will increase k. According to these clues, the value of k may be estimated roughly. In a practical setting, a key piece of information that enables the estimation is the content in the Web-pages and their number that the user consults for product comparison. For evaluation scale size ν, on the other hand, it may be possible to learn the relationship between the value of ν and personal characteristics like eWOM involvements and product expertise by doing examinations presented in [36], which is also discussed in Section III. B., on a large scale.

The P-Maps developed in Section V can be regarded as unexplored sub-hypotheses derived from the generalized hypothesis described in Section II. C. Therefore, future work must determine whether the potency-magnitude relations change as the maps predict. The observation of the reversal phenomenon is particularly important; whether the potency-magnitude relation of the two messages is reversed when scale size ν becomes larger.

To obtain accurate potency predictions, not only the inference quantum proposed in this paper but also many other factors of eWOM messages, such as those discussed in [39]–[41], have to be considered. The combination of factors will determine the potency of the eWOM messages, so these factors should be used properly for practical prediction methods.

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