Measuring Bidirectional Subjective Strength of Online Social Relationship by Synthetizing the Interactive Language Features and Social Balance (Short Paper)

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Abstract. In online collaboration, instead of the objective strength of social relationship, recent study reveals that the two participants can have different subjective opinions on the relationship between them, and the opinion can be investigated with their interactive language on this relationship. However, two participants' bidirectional opinions in collaboration is not only determined by their interaction on this relationship, but also influenced by the adjacent third-party partners. In this work, we define the two participants' opinions as the subjective strength of their relationship. To measure the bidirectional subjective strength of a social relationship, we propose a computational model synthetizing the features from participants' interactive language and the adjacent balance in social network. Experimental results on real collaboration in Enron email dataset verify the effectiveness of the proposed model.

Keywords: Social relationship · Subjective strength · Interactive language · Balance theory

1 Introduction

To recognize the strength of interrelationships is very essential in online collaboration [1] which have two primary options: The first one is regarding the strength of interrelationships as objective properties, which can be investigated independently of the participants' subjective opinions. The second option is to determine the strength according to two participants' subjective opinions bidirectionally. Recent study [2] indicates that the objective measurement often leads to symmetric values of the interrelationships' properties, while the subjective measurement can leads to asymmetric values, because two participants may have different opinions on their interrelationship's strength. The measurement of this kind of asymmetric and subjective strength is necessary in many social studies. For example, in influence analysis, the possibility of the information spreading is not identical on two directions: the individual who regards their interrelationship is strong will communicate more frequently, while the other individual who regards the interrelationship is weak will do the opposite (Fig. 1).

H. Gao et al. (Eds.): CollaborateCom 2018, LNICST 268, pp. 112–123, 2019.
https://doi.org/10.1007/978-3-030-12981-1_7

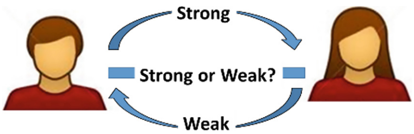


Fig. 1. The undirected objective strength and bidirectional subjective strength in social relationship. The undirected objective strength is unable to distinguish the participants' different opinions on each other.

The interaction on the social relationship is an important indicator of the properties of the relationship [3]. To investigate the bidirectional subjective strength of the social relationship, current studies indicate the ability of interactive language in revealing the participants' opinions. The interactive language is the language used by the two participants' for the communication on their relationship. However, the subjective strength in collaboration is not only determined by their interaction on this relationship, but also influenced by the adjacent third-party partners. Wang et al. [2] finds that the interactive language features on a social relationship can be correlated to the neighbor topological features in social network.

To improve the measurement of the bidirectional subjective strength of social relationships, in this work, we propose a computational model synthetizing the features from participants' interactive language and the neighbor topological features in social network. Firstly, inspired by the sociolinguistics, we select four typical interactive language features which indicate the frequency, quantity, quality and emotion of interactive language, respectively. Secondly, according to the balance theory in sociology, we introduce the requirement of the triangle balance among social relationships into the subjective strength measurement. Finally, to combine the proposed language and topological features, we improve an optimization process to derive the bidirectional subjective strength synthetizing the interactive language features and the social balance. The experimental results on real collaboration among Enron email users show that the performance of the proposed model exceed the models using language features independently.

2 Related Work

2.1 Symmetric and Asymmetric Analysis of Social Interrelationships

Many early studies suppose that the properties of interrelationships are symmetric. The concept of the strength of social relationship is firstly explained by Granovetter et al. [4]. The topological features e.g., the balance of the triangular closure, are most widely used to measure the strength of social relationship [5]. In recent studies, behavior feature is popular in measuring symmetric strength of social relationship [6–8]. The content information of social language are also considered, for example Adali et al. [9] applied symbolic words in the interaction, but this work does not involve deeper language features.

There are also some recent studies analyzed the social relationship directionally or asymmetrically in a sense. For directed relationships, Leskovec et al. [10] firstly considered an explicit formulation of the sign prediction problem. West et al. [11] developed a model to predict the polarity of person-to-person evaluations. This work focused on bidirectional evaluation between two individuals which are naturally asymmetric and was an important base of our approach. As an alternation of this work, in this paper, we focus on the bidirectional subjective strength of interrelationship, instead of the bidirectional sentiment evaluation. To distinguish the sentiment evaluation and subjective strength, we replace the sentiment feature with the interactive language features related to the subjective strength, which is inspired by the sociolinguistics. Furthermore, we extend the model on a directed graph instead of the undirected graph.

2.2 Synthesis of Social Language and Social Network Analysis

In recent studies, natural language processing and social networks analysis are often combined to understand the nature of social relationship, user profile or social event. Adali et al. [9] showed that the feature sets from social behavioral information and textual information are practically equivalent in terms of their ability to determine the different types of relationships. Bramsen et al. [12] presented a text corpus-based statistical learning approach to model social power relationships. Thomas et al. [13] capitalized on this insight using an elaboration of the graph-cuts approach of Pang and Lee [14]. Tan et al. [15] used Twitter follows and mentions to predict attitudes about political and social events. Related ideas are pursued by Ma et al. [16] and Huang et al. [17], who add terms to their models enforcing homophily between friends. West et al. [11] developed a model that synthesizes textual and social-network information to jointly predict the polarity of person-to-person evaluations.

Compared with state-of-the-arts works synthesizing the language and network features, we propose to combine the two kinds of features to identify the bidirectional subjective strength of social interrelationship, instead of measuring the strength from an objective view. In the following sections, we will firstly introduce our selection and calculation of the features from the interactive language on social relationships. Then, we will explain our extension of the tradition balance theory in this work, and how to combine the extended balance with the language features in the measuring of the subjective strength.

3 Characterize Subjective Opinions on the Strength of Interrelationship with Interactive Language Features

To describe the individuals' opinions on their interrelationship's strength asymmetrically, some studies choose to use objective features directionally, e.g., the communication frequency in two directions. Though some objective features can be used asymmetrically, they cannot describe the subjective opinions accurately. Therefore, a more reasonable solution is to measure the opinions with subjective features.

Among the available resources, interactive language features are good choices, which are not only closely related to the properties of interrelationship, but also highly descriptive of individuals' opinions. In this section, inspired the theory from sociolinguistics, we propose four typical features of interactive language to measure the subjective strength of social relationship.

3.1 Interactive Language Features from Sociolinguistics

In sociolinguistics, the theory of communicative action [18] proposes to reconstruct the concept of relationship with the communicative act, instead of the objectivistic terms. The linguistic structures of communication can be used to understand the social relationships. Sapir-Whorf hypothesis [19] also supposes that the semantic structure of the language using shapes or limits the ways in which a speaker forms conceptions of the world including the social relationships. In the communication, people's choice of words is always highly depending on their subjective opinions on their interrelationship with the others. The theories inspire us to assume that one's opinion on an interrelationship's strength can impact his language using in communication. Consequently, we can measure the subjective strength of one's relationship according to his language features in interaction. The next problem is which language features should be selected? In sociolinguistics, Holmes [20] introduces four important dimensions to study the language using in social communication:

(1) The solidarity-social distance scale: concerned the solidarity of the individuals' relationship in social communication.
(2) The social status scale: concerned the relative status of the individuals' relationship in social communication.
(3) The formality scale: concerned the formality of language using in different relationships, topics and places.
(4) The referential and affective scale: concerned referential and affective function of the language in social communication.

The first two dimensions concerned the features of social interrelationship from both subjective and objective views. The last two dimensions concerned the features of interactive languages, which are highly related to social interrelationship.

According to Holmes' dimensions, we propose four typical linguistic features of interactive languages to measure an individual's subjective opinion on his interrelationship's strength. The designed features are frequency, length, fluency and sentiment polarity which indicate quantity, quality and emotion of interactive language, respectively. Among the features, the frequency and length are two primary features of language communication, and the fluency and sentiment corresponds to the formality and affective scale mentioned in Holmes' theory, respectively. The following are the detailed explanation of the four features:

(1) The frequency is the times of communication within a period of time, which is supposed to reflect one's intention of the communication on an interrelationship.

(2) The length is the number of the words of interactive language, which is also supposed to reveal one's intention of the communication.
(3) The fluency is the formality and quality of interactive language which is supposed to reveal whether the speaker treats a relationship seriously or not.
(4) The sentiment polarity measures the emotion tendency of interactive language which is supposed to have a positive correlation with the personal opinion on interrelationship, i.e., more positive emotion in interactive language often indicate that the interrelationship is more valuable to the speaker.

It is noted that all these four features can be recognized by the state-of-the-arts natural language processing technologies, which will be illustrated in the experiments in Sect. 5.

3.2 Distinguish the Asymmetry of Opinions from the Asymmetry of Language Habits

Though one's interactive language style is closely related to his opinions on his interrelationships' strength, it is inexact to understand the opinions using the original values of language features directly. Actually, in natural language understanding, the meaning of the language is always not only determined by the content, but also by the context.

The context of the interactive language is very complex. In this work, we focus on how to understand one's opinion more accurately considering his personal habit in language using. For example, suppose *A* is a very negative person, and he always talks to person *B* with the language whose sentiment score is negative. But we also know that *A* talks to everybody very negatively and he talks to *B* most friendly compared with the others. In this case, if we want to measure the *A*'s opinion on his relationship with B correctly using sentiment polarity score, we need to normalized the scorer according to *A*'s personal language habit, instead of using the original absolute value.

To normalize one's opinion according to his personal language habit, we utilize the strategy in [2]. Given an individual *I*, we normalize *I*'s each language feature score f with *I*'s personal language habit value $H_f(I)$. $H_f(I)$ is measured by Formula (1), where $f(I, I_i)$ is the feature value f of the language said by *I* to another individual I_i, and *C* is the set of all individuals who is in communication with *I*.

$$H_f(I) = \frac{1}{|C|}\sum\nolimits_{I_i \in C} f(I, I_i) \tag{1}$$

Then $f'(I, I_i)$ is calculated with Formula (2) as the normalized value of $f(I, I_i)$ according to *I*'s personal language habit:

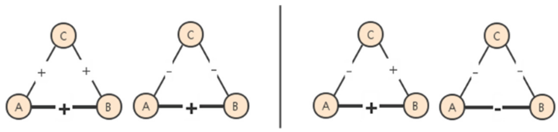
$$f'(I, I_i) = \frac{f(I, I_i) - H_f(I)}{H_f(I)} \tag{2}$$

4 Synthetizing the Language Features and Social Balance to Measure the Bidirectional Subjective Strength

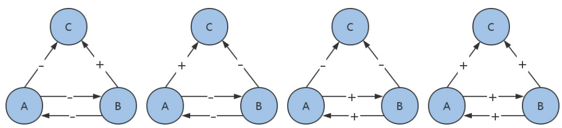
In this section, we formulate a computational model to measure the asymmetric and subjective strength of interrelationship bidirectionally, synthesizing four proposed interactive language features and an extend version of the traditional balance theory.

4.1 Theory of Social Balance and the Extension

Theory of social balance [21] is popular in social network studies. This theory is based on the homogeneity assumption, which states that, in a social triangle, the more similar two individuals' opinions on the third one are, the more positive their interrelationship will be, and vice versa. Figure 2(a) illustrates the balanced and unbalanced triangles in traditional balanced theory, tagging the relationship with '±'. The balance theory is often extended in social relationship studies to meet the requirement of particular task [22]. In this work, for directional measuring, we extend the traditional balance theory to directed triangles according to homogeneity assumption, as shown in Fig. 2(b). In this extended version, all the interrelationships are directed, and four directed interrelationships are considered in the balance identification: the bidirectional relationships between the two participants (i.e., *A* and *B*) and two participants' relationships towards the third-party individual (i.e., *C*). In a directed social triangle, the criterion to identify the balance status is redefined sharing the same principle of the traditional balance theory, i.e., the principle of the homogeneity assumption.



(a) Balanced (left two) and unbalanced (right two) triangles in balance theory



(b) Balanced triangles in extended balance theory

Fig. 2. Traditional and extended social balance theory on undirected and directed triangles.

4.2 Measuring Bidirectional Subjective Strength

In this work, we modify the model in [11] to deal with the bidirectional subjective strength measurement replacing the sentiment features with interactive language features and extending the undirected graph to directed graph. In the new model, a social network is modeled as a directed graph $G = (V, E, s)$, where V is the set of individuals; E is the directed interrelationships between the individuals; and the real value set $s \in [0, 1]^{|E|}$ is the subjective strength values on each directed interrelationship. A directed triangle $t = \{e_{AB}, e_{BA}, e_{AC}, e_{BC}\}$ is a set of four directed interrelationships in E, and T is the set of all the t in G. $s_t = (s_{AB}, s_{BA}, s_{AC}, s_{BC})$ is the set of the subjective strength values on each interrelationship in t. For each directed interrelationship e, $\{f1_e, f2_e, f3_e, f4_e\}$ is the values of four proposed interactive language features of e, i.e., frequency, length, quality and sentiment. Then, together with the feature of social balance, we can calculate the bidirectional strength with an optimizing process. The process try to find the final strength $s*$ by meeting the linguistic and topological measurement as Formula (3)

$$s^* = \underset{s\in[0,1]^{|E|}}{argmin} \sum\nolimits_{e\in E, f_e\in\{f1_e, f2_e, f3_e, f4_e\}} c(s_e, f_e) + \sum\nolimits_{t\in T} d(s_t) \tag{3}$$

In Formula (3), the first term is the linguistic cost representing the difference between the bidirectional strength s_e and the linguistic features f_e which is illustrated as formula (4).

$$c(s_e, f_e) = \lambda_1(1 - f_e)s_e + \lambda_0 f_e(1 - s_e) \tag{4}$$

In Formula (4), $\lambda_1, \lambda_o \in R_+$ are parameters tuning the costs for higher or lower strength, respectively. The second term is the topological cost representing how unbalanced the triangle is with the bidirectional strength s_t. of four directed edges. This cost is calculated as the difference between s_t and most similar balanced triangle.

The problem in Formula (3) is NP-hard. Adopting the strategy in [11] based on hinge-loss Markov random field, this problem can be relaxed by using sums of hinge loss terms to modify c in Formula (3) over the continuous domain [0, 1] and d in Formula (3) over $[0, 1]^4$. As a result, the hinge-loss Markov random field formulation is equivalent to Formula (3). The relaxation can be illustrated as Formula (5)

$$\widetilde{c}(s_e, f_e) = \lambda_1||s_e - f_e||_+ + \lambda_0||f_e - s_e||_+ \tag{5}$$

where $||y|| + = max\{0, y\}$ is the hinge loss. For each $s_t \in [0, 1]^4$, we rewrite $d(s_t)$ as a convex surrogate:

$$\tilde{d}(s_t) = \sum\nolimits_{z\in\{0,1\}^4} F(s_t, z) \tag{6}$$

where,

$$F(s_t, z) = \begin{cases} t_1 * [1 - f(s_t, z)],\ z\, is\, a\, balanced\, triangle \\ t_2 * f(s_t, z),\ Other \end{cases} \tag{7}$$

Here, t_1, $t_2 \in R_+$ are tunable parameters, where

$$f(s_t, z) = \left|\left|1 - ||s_t - z||_1\right|\right|_+ \tag{8}$$

where, $||s_t - z||_1 = \sum_{i=1}^{4} |s_i - z_i|$ is the degree that s_t different from a directed triangle z. Intuitively, the more the inferred directed triangle strength s_t different from a balanced triangle, the higher the directed triangle costs. Thus, the objective function of optimization problem is the following relaxation of Formula (3) which can be efficiently optimized:

$$s^* = \underset{s \in [0,1]^{|E|}}{argmin} \sum\nolimits_{e \in E, f_e \in \{f1_e, f2_e, f3_e, f4_e\}} \tilde{c}(s_e, f_e) + \sum\nolimits_{t \in T} \tilde{d}(s_t) \tag{9}$$

5 Experiments

In this section, we evaluated the proposed model's ability in measuring the bidirectional degrees of individuals' opinions on their interrelationships' strength, i.e., the subjective strength. In particular, we try to use the proposed model to identify the bidirectional subjective strength of the superior-subordinate relationships between Enron email users. We describe the data setting, ground truth and the calculation of the interactive language features of the experiments. Then, we compare the performance of proposed synthetized model with that of the models only using language features.

5.1 Experimental Setup

Data Setting: We utilized the Enron email dataset, which contains 0.5M mails among employees. We retained only those interrelationships where at least 15 emails were sent in each direction. The filtered set contains 1078 interrelationships between 647 individuals. In the filtered set, we obtain the organizational hierarchy of 232 Enron employees provided by Agarwal [23]. From this dataset, 70 pairs of the superior-subordinate relationships are manually exploited consists of 80 nodes and 140 directed edges. We conducted experiments with the proposed model (Formula (9)) synthetizing normalized pair-wise language features (Formula (2)) and directed triangles of interrelationships.

Ground Truth: To find the ground truth of individuals' exact opinions on their interrelationships' strength is difficult. We intuitively make the assumption that in a superior-subordinate relationship, two participants' opinions on their interrelationship are asymmetric. The individual of lower position tend to put more importance on their interrelationship than the individual of higher position does. We use this assumption as the ground truth to evaluate the proposed models' ability in measuring asymmetric opinions on interrelationship's strength in superior-subordinate relationship.

Language Features Calculation: For each directed pair of individuals $<I_i, I_j>$, four linguistic features are calculated with the emails' content sent from I_i, to I_j, to characterize I_i's opinion on his interrelationship towards I_j as the method in [2]:

(1) "Frequency": average emails count per day from I_i to I_j.
(2) "Length": average words count per email from I_i to I_j.
(3) "Quality": average perplexity score per sentence in the emails from I_i to I_j. Higher perplexity score means lower language quality. The perplexity score is calculated by the SRI language modeling toolkit[1] (SRILM).
(4) "Sentiment": average sentiment score per word in the emails from I_i, to I_j. A sentiment dictionary[2] is used to score the positive, negative and neuter words as 1, −1 and 0, respectively.

5.2 Performance Comparison

In the experiments, given a pair of individuals *A* and *B* engaged in a superior-subordinate relationship where *A* is the one of lower position, *score_A* and *score_ B* are the degree of *A* and *B*'s opinion on their interrelationship's strength measured by the proposed model, respectively. If *score_A – score_B > threshold*, we regard the measurement on this pair to be successful, i.e., the individual of lower position (*A*) puts more importance on their interrelationship than the individual of higher position (*B*). We tried the *threshold = 0, 0.01, 0.05, 0.1*, respectively. The threshold is supposed to tune the model slightly. A too large threshold bring unnecessary manual influence to the model.

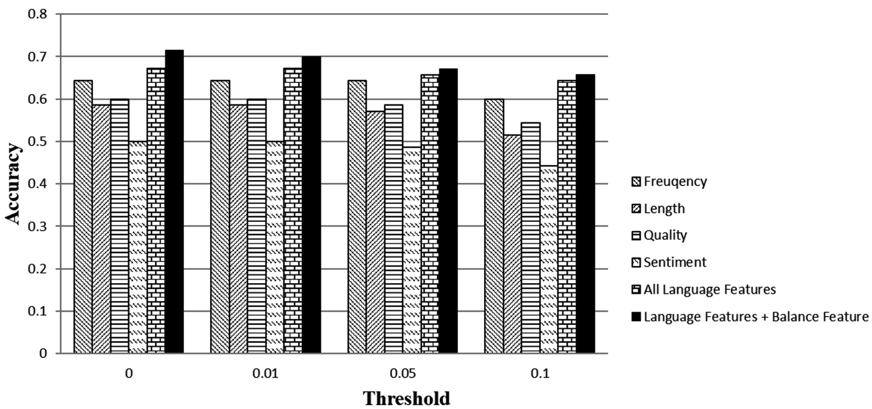


Fig. 3. The performance of single and synthetized models in measuring the asymmetric subjective strength on superior-subordinate relationship in Enron email dataset.

[1] http://www.speech.sri.com/projects/srilm/.
[2] http://www.keenage.com/download/sentiment.rar.

The experimental results are shown in Fig. 3. The X-axis is the value of thresholds and the Y-axis is the precision of measurement. In comparison, the results measured by single language features are noted by the names of features, i.e., 'Frequency', 'Length', 'Quality' and 'Sentiment'; the result of proposed model synthetizing only four language features is noted as 'All Language Features'; the proposed model synthetizing language and social balance features is noted as 'Language Features + Balance Feature'.

In Fig. 3, the 'All Language Features' model outperforms all single features on all thresholds. Furthermore, when synthetized with balance feature, the performance of 'Language Features + Balance Feature' model exceeds the 'All Language Features' model. This result illustrates the effectiveness of the proposed model in measuring the bidirectional subjective strength of the social relationships. The key advantage is to synthetize the features from interactive language and social balance.

6 Conclusions

In this paper, we measured bidirectional subjective strength of social relationship in online collaboration, i.e., individuals' asymmetric opinions on their interrelationships' strength, with the help of interactive language features and the balance of social network. According to sociolinguistics theories, we adopted four typical language features to represent one's opinion on their relationships' strength, representing the frequency, length, quality and sentiment of the language. We also extend the traditional undirected balance theory to a directed version to meet the requirement of bidirectional strength measurement.

Synthesizing the designed language and balance features, we extend the state-of-the-arts model to measure the bidirectional subjective strength of social relationship. Using superior-subordinate relationship among Enron email users as ground truth, as a case study, we verified the effectiveness of the proposed model in measuring the asymmetric strength of social relationship from a subjective view. In the experiments, the synthesized model outperformed the baselines using combined or single language features.

Our experimental research illustrate the solution to measure the individuals' asymmetric opinions on their interrelationships' strength, and potentially leads to a promising direction to model the social relationship from a subjective view. In the future work, we will try to profile the opinion on interrelationship with more detailed information using the content of interactive language.

Acknowledgments. This work is supported by National Natural Science Foundation of China (U1736103), National Natural Science Foundation of China (Key Program, U1636203), the state key development program of China (2017YFE0111900) and National Natural Science Foundation of China (61472277).

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