Current Attitude Prediction Model based on Game Theory

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Abstract. Social interactions on online communities involve both positive and negative relationships: people give feedbacks to indicate friendship, support, or approval; but they also express disagreement or distrust of the opinions of others. One's current attitude to the other user in online communities will be affected by many factors, such as the pre-existing viewpoints towards given topics, his/her recent interactions with others and his/her prevailing mood. In this paper, we develop a game theory based method to analyze the interactive patterns in online communities, which is the first in its kind. The performance of this prediction model has been evaluated by a real-world large-scale comment dataset, and the accuracy reaches 82%.

Keywords: online community; relationship; current attitude; game theory.

1 Introduction

Traditional online community researches have mainly considered positive relationships only. Most of those researches focus on the friend-networking sites, such as MySpace, Facebook, and Google+ [2-4]. Negative relationships are seldom found on those sites, because the interactive users might be friends in real world. Recently a number of researchers have begun to investigate negative as well as positive relationships in online communities. For example, users on Wikipedia can vote for or against the nomination of others [5]; users on Epinions can express trust or distrust of others [6]; and participants on Slashdot can declare others to be either "friends" or "foes" [7]. However, all of the above works exhibit a common problem -the lack of explicit labeling, making it difficult to reliably determine the sentiment of a given interaction.

A few recent studies examined the interactive patterns using data that can be gathered from online communities, for instance, writing messages to other users [1, 11-12, 15-17]. In our most recent study [1, 10], we roughly identify several terms or phrases from the public discussions as either supportive or opposing. Every term/phrase is assigned with a value between 0 and 1 according to their tone manually. A higher value corresponds to a greater degree of support; if the phrase is neutral, we assigned it a value of 0.5. Thus, every phrase has an associated numerical "trust".

adfa, p. 1, 2011.

For a given comment from one ID to the other, we can determine the implicit orientation by counting the number of positive or negative words in it (if there are several emotional words in one comment, we take the average).

Accordingly, the **semantic strength** from user i to user j under a given topic p can be calculated as:

$$s^p(i,j) = (\sum_{k=1}^{n_{i,j}^p} s^p(i,j,k)) / (n_{i,j}^p) \qquad (1)$$

Where $s^p(i,j,k)$ is the implicit orientation of one comment from i to j under the topic p, and $n_{i,j}^p$ is reply number from i to j under the topic p.

In reality, one's current attitude to the other user in online communities will be affected by many factors, such as the pre-existing viewpoints towards given topics, his/her recent interactions with others and his/her prevailing mood. In this paper, we develop a game theory based method to analyze the interactive patterns in online communities, which is the first in its kind. Our contributions are as follow:

1) In online communities, if both users A and B send a positive comment, then their happiness will get a positive promotion. If just user A sends a positive comment (user B sends a negative comment), user A's happiness will decrease, and the happiness of user B will increase. Finally, if both users A and B send a negative comment to each other, their happiness will get a negative promotion. Therefore, we can model the user interaction as a game, in which, the two players are solely concerned with maximizing their own payoffs. In the end of this game, user A will choose the optimal strategy to maximize his/her own payoff. The optimal strategy taken by user A can be used to predict his/her current attitude to user B.
2) To evaluate the performance of our current attitude prediction model, we crawled the comment data from Tianya website, and built a test set according to existing user discussion lists. The accuracy of our model in predicting one's current attitude to the other is 82%.

2 Game theory based user interaction model

Suppose that user A is an online community user, he can interact with other users by writing comments to each other. If user A sends a positive comment to user B, user B might give user A a feedback, which user A hopes is also positive. In this case, the happiness user A received will be mainly decided by the implicit orientation of the comment from user B to user A, which is $s(B,A)$. While if user A sends a negative comment to user B, user A might not look forward a positive feedback from user B. The happiness user A gets will be mainly decided by the attitude to user B of himself. For instance, A is strongly against user B, the semantic strength $s(A,B)$ from user A to user B will be very low. In this case, user A's happiness will be measured as $1-s(A,B)$. Thus, user A has two possible options for how to behave: to send a positive comment, or to send a negative one. The challenge in reasoning about this is that the happiness of user A in online communities with the outcome depends not just on his own decisions but on the decisions made by every participant. Therefore, the interactive users constitute a complete description of each player's happiness with each of the possible outcomes of a game. In the end of this game, user A will choose his optimal strategy to maximize his own happiness. The optimal strategy taken by user A will be used to measure the current attitude from him to user B.

2.1 Interactive game model

Game theory is a study of strategic decision making. More formally, it is the study of mathematical models of conflict and cooperation between intelligent rational decision-makers [13]. A game consists of three components: a set of players, the strategy set for each player and a utility function for each player measuring the degree of "happiness" of the player. Then, we can use a tuple $G = [\kappa, \{A_k\}, R_k]$ to represent a game, where $\kappa = \{1, ...K\}$ is the set of players, A_k is the set of actions (strategies) available to user k, and R_k is the utility function for user k. Taking the above user interaction as an example, there are two players which are A and B. And their sets of actions are the same which are to send a positive comment, or to send a negative one. The basic utility functions for user A are $s(B, A)$ or $1 - s(A, B)$ which depends on the decisions made by everyone. The situation is symmetric when we consider the basic utility of user B. The underlying principles of user interactions in online communities are as follow: if both users A and B send a positive comment, then their payoffs will get a positive promotion. If just user A sends a positive comment (user B sends a negative comment), user A's payoff will decrease, and the payoff of user B will increase. Finally, if both users A and B send a negative comment to each other, their payoffs will get a negative promotion. As one's pre-existing viewpoints towards given topics and emotional changing are hard to capture, in this paper, both positive and negative promotions of payoff will be randomly assigned in a given range.

There is a simple tabular way to summarize all these outcomes, as follows. We represent user A two choices-to send a positive comment, or to send a negative comment-as the rows of a 2×2 table. We represent user A's partner's user B two choices as the columns. So each box in this table represents a decision by each of the two users. In each box, we record the happiness/payoff they each receive: first user A's, then user B's. Writing all this down, we have the table shown in Fig. 1. Now user A needs to figure out what to do: sends a positive comment, or sends a negative one. Clearly, user A's happiness/payoff depends not just on which of these two options he choose, but also on what user B decides. Therefore, as part of user A's decision, A has to reason about what user B is likely to do. Thinking about the strategic consequences of his own actions, where user A needs to consider the effect of decisions by user B. Our interest is in reasoning about how users in online communities will behave in this interactive game.

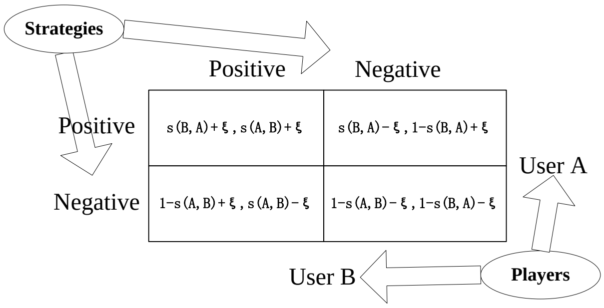


Fig. 1. User interaction model based on game theory

2.2 Optimal strategy

Once the payoffs have been defined, interactive users will select their optimal strategies according to the above three assumptions. If a_A^i, $a_A^i \in A_A$ is a strategy chosen by user A, and a_B^j, $a_B^j \in A_B$ is a strategy chosen by user B, then there is an entry in the payoff matrix corresponding to the pair of chosen strategies (a_A^i, a_B^j). We will write $R_A(a_A^i, a_B^j)$ to denote the payoff to user A as a result of this pair of strategies, and $R_B(a_A^i, a_B^j)$ denote the payoff to user B as a result of this pair of strategies. Then, we used two fundamental concepts that will be central to our discussion of the interactive game.

The first concept is the idea of **a (strict) best response**: it is the best choice of one user, given a belief about what the other player will do. In our interactive game, we say a strategy a_A^* for user A is **a (strict) best response** to a strategy a_B^j for user B is a_A^* produces at least as good a payoff as any other strategy paired with a_B^j:

$$R_A(a_A^*, a_B^j) \geq R_A(a'_A, a_B^j) \qquad (2)$$

$$R_A(a_A^*, a_B^j) > R_A(a'_A, a_B^j) \qquad (3)$$

for all other strategies a'_A of user A. When A has a strict response to a_B^j for user B, this is clearly the strategy s/he should select when faced with a_B^j.

The second concept is the idea of **a (strictly) dominant strategy**. We say that a dominant strategy of user A is a strategy that is a best response to every strategy of user B:

$$R_A(a_A^*, a'_B) \geq R_A(a'_A, a'_B) \qquad (4)$$

$$R_A(a_A^*, a'_B) > R_A(a'_A, a'_B) \qquad (5)$$

Thus, we made the observation that if a user has a strictly dominant strategy, then we can expect him/her to use it. As shown in Fig. 2, suppose user A posted a topic, in which he called on China government to implement quality education. User B met this post and discussed with him about this topic. In their recent interaction, user B sends a comment, the semantic strength of which is $s^p(B, A, t)$, then user A gives a feedback to user B, the semantic strength of this feedback is $s^p(A,B,t)$. How should user B do next? In this case, user B may meet three different situations: 1) a game in which user B has a strictly dominant strategy; 2) a game in which only user A has a strictly dominant strategy; 3) a game in which neither user has a strictly dominant strategy. We will respectively discuss these three situations next.

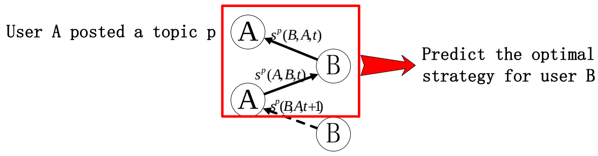


Fig. 2. An example of the recent interaction between user A and user B

2.2.1 A game in which user B has a strictly dominant strategy

Suppose user B sends a positive comment to user A to express her agreement. Taking the semantic analysis of her comment as in [1, 12], we learn that the semantic strength from B to A is 0.8. Then, user A also sends a positive comment to user B, in which he gave B a good compliment, the semantic strength from A to B is 0.7. According to the interactive model in Section 2.1, we can capture this situation with numerical payoffs as shown in Fig. 3(a). ξ represents the positive and negative promotions of payoff decided by their pre-existing viewpoints towards given topics and prevailing moods. As one's pre-existing viewpoints towards given topics and emotional changing are hard to capture, in this paper, both positive and negative promotions of payoff will be randomly assigned in a given range. In this example, we unified set ξ as 0.1, and the final payoff table will be acquired as shown in Fig. 3(b).

User A \ User B	Positive	Negative
Positive	$0.8+\xi, 0.7+\xi$	$0.8-\xi, 1-0.8+\xi$
Negative	$1-0.7+\xi, 0.7-\xi$	$1-0.7-\xi, 1-0.8-\xi$

(a)An interactive game about the topic of "quality education"

User A \ User B	Positive	Negative
Positive	0.9, 0.8	0.7, 0.3
Negative	0.4, 0.6	0.2, 0.1

(b)The final payoff table with ξ =0.1

Fig. 3. A game in which user B has a strictly dominant strategy, the strategy pair in red box represents the optimal strategy pair.

As $R_B(Positive, Positive) > R_B(Postive, Negative)$ and $R_B(Negative, Positive) > R_B(Negative, Negative)$, to send a positive comment is a strictly dominant strategy for user B. So it is easy to reason about what user B is likely to do.

2.2.2 A game in which only user A has a strictly dominant strategy

There are many situations where the structure of the game and the resulting behavior looks very different. Indeed, even simple changes to a game can change it from the above interactive game to something more benign. For example, suppose that user B also sends a positive comment to user A, and additionally gave a few supplemental points. The semantic strength from user B to user A is 0.7. However, user A sends a negative feedback to user B, because he thinks that the supplemental points are not reasonable. In this case, the semantic strength from user A to user B is 0.3. The numerical payoffs in this situation are captured as shown in Fig. 4(a). This time, we randomly assign a value between 0 and 0.2 to ξ. Then we can check that the payoff matrix has changed as shown in Fig. 4(b).

Furthermore, we can check that with these new payoffs, user B does not have a strictly dominant strategy. However, user A has a strictly dominant strategy. Still, it is not hard to make a prediction about the outcome of this game. Since user A has a strictly dominant strategy, we can expect he will play it. Now, what should user B do? If user B knows user A's payoffs, and know that user A wants to maximize her happiness/payoff, then user B can confidently predict that user A will send a negative comment to her. Then, since to send a negative comment is the strict best response by user B when user A sends a negative comment, we can predict that user B will send a negative comment. So our overall prediction of interaction in this game is to send a negative comment by user B.

User A \ User B	Positive	Negative
Positive	0. 7+ξ , 0. 3+ξ	0. 7−ξ , 1−0. 7+ξ
Negative	1−0. 3+ξ , 0. 3−ξ	1−0. 3−ξ , 1−0. 7−ξ

(a)An interactive game about the topic of "quality education"

User A \ User B	Positive	Negative
Positive	0. 8, 0. 5	0. 5, 0. 4
Negative	0. 9, 0. 1	0. 6, 0. 2

(b)The final payoff table where ξ is randomly assigned in a given range of (0, 0.2)

Fig. 4. A game in which only user A has a strictly dominant strategy, the strategy pair in red box represents the optimal strategy pair.

2.2.3 A game in which neither user has a strictly dominant strategy

When neither user in the interactive game has a strictly dominant strategy, we need some other way of predicting what is likely happen. Let's return to our pervious user interactive game, and see a special situation. Suppose user B sent a neutral comment, the semantic strength of which is 0.5, to user A. Then user A also sent a neutral comment to user B. Then, the initial numerical payoff matrix is captured as shown in Fig. 5(a). We still randomly assign a value between 0 and 0.2 to ξ and the final numerical payoffs as shown in Fig. 5(b).

If we study how the payoffs in this example, we see that neither user has a dominant strategy. So how should we reason about the outcome of play in this game?

A complete definition of how a player will play a game will be called a **pure strategy**. For a two-player game, if there is a strictly dominant strategy, we can find the pure strategies of both players. However, if neither user has a strictly dominant strategy, we should consider the **mixed strategies**. In this model, the possible strategies of user A are numbers p between 0 and 1, and p means that user A is committing to send a positive comment with the probability p, and to send a negatvie one with the probability 1-p. Similarly, the possible strategies for user B are numbers q between 0 and 1. Once we have done this, we can then rank outcomes accoding to their associated number. As in this example, if user A chooses to send a positive comment while user B chooses a probability of q, then the expected payoff to user A is

$$E_A(Positive) = (0.7)(q) + 0.3(1-q) = 0.3 + 0.4q \qquad (6)$$

Similarly, if user A chooses to send a negative comment while user B chooses a probability of q, then the expected payoff to user A is

$$E_A(Negative) = (0.6)(q) + 0.4(1-q) = 0.4 + 0.2q \qquad (7)$$

Then we can get the unique Nash equilibrium [14] for the miexed-strategy (the **Mixed- Strategy Equilibrium**) for this example, just have

$$E_A(Positive) = E_A(Negative) \qquad (8)$$

User A \ User B	Positive	Negative
Positive	0. 5+ξ, 0. 5+ξ	0. 5−ξ, 1−0. 5+ξ
Negative	1−0. 5+ξ, 0. 5−ξ	1−0. 5−ξ, 1−0. 5−ξ

(a)An interactive game about the topic of "quality education"

User A \ User B	Positive	Negative
Positive	0. 7, 0. 7	0. 3, 0. 6
Negative	0. 6, 0. 3	0. 4, 0. 4

(b)The final payoff table where ξ is randomly assigned in a given range of (0, 0.2)

Fig. 5. A game in which neither user has a strictly dominant strategy, the strategy pairs in red box are Nash equilibriums

or in other words q=0.5. The situation is symmetric when we consider things from user B's point of view, and evaluate the payoffs from a play of probability p by user A. We also have p=0.5. Thus, the pair of strategies p=0.5 and q=0.5 is the only possibility for a Nash equilibrium. In his famous paper [14], John Forbes Nash proved that there is an equilibrium for every finite game.

Above all, we analyze all the three suitations in the two-player interavtive game. We can get a pair of pure strategies in the first two suitations, and get a pair of mixed strategies in the last suitations. The optimal strategy taken by user B can be used to predict her current attitude to user A.

2.3 Relationship predication

The interactive game in online environment has a feature that the two interactive users will choose their actions independently accoding to their recent interacions. That means, their actions are not simultaneously given. As shown in Fig. 6, user A posts a topic p, then a reply article from user B commnets on this topic so as to continue the discussion. The semantic strengths between these two users are sited on every directed link. At the end of their discussion about this topic, we can predict the optimal strategy (to send a postive comment, or to send a negative comment) for user A by considering his latest interactions with user B, which are $s^p(A,B,n^p_{A,B})$ and $s^p(B,A,n^p_{B,A})$. We can also predict the optimal strategy for user B by considering interctions $s^p(B,A,n^p_{B,A}-1)$ and $s^p(A,B,n^p_{A,B})$. Actually, we have already known the strategy for user B as is sited on the last link of this discussion. We can use $s^p(B,A,n^p_{B,A})$ to verify the performance of our interactive game model. Similarly, we can use one's $t+1$th action to verify the performance of the interactive game model in the tth interaction with his/her partner. The overall performance of our interactive game model will be discussed in Section 3.

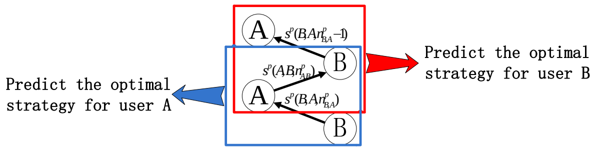


Fig. 6. User interactions under a given topic p in online environment

3 User interactions in a real online community

As we stated in Section 2.3, we can use one's $t+1$th action to verify the performance of the interactive game model in the tth interaction with his/her partner. Then, we can build a test set according to existing user interaction history. Let's go back to the user interaction example in Section 2.3, we assume that user A will send only one comment to user B if s/he receives the recent feedback from user B. Thus, we can predict user A's $t^p_{A,B}+1$th action using the interaction game model in Section 2.2 based his recent interactions with user B, namely $s^p(A,B,t^p_{A,B})$ and $s^p(B,A,t^p_{B,A})$. In this case, user A will have an optimal strategy, $optimal\_strategy^p(A,B,t^p_{A,B}+1)$.

We can compare $optimal\_strategy^p(A,B,t^p_{A,B}+1)$ with $s^p(A,B,t^p_{A,B}+1)$ using a simple judgment function, which is:

$$\delta(x,y)=\begin{cases}1 & x\geq 0.5, y\geq 0.5\ or\ x\leq 0.5, y\leq 0.5\\ 0 & otherwise\end{cases} \tag{9}$$

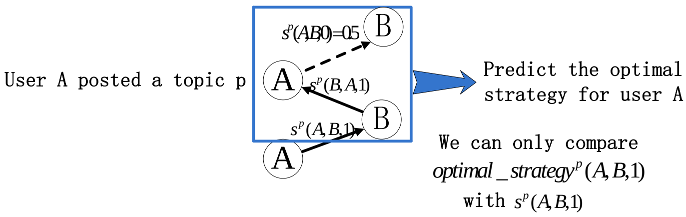
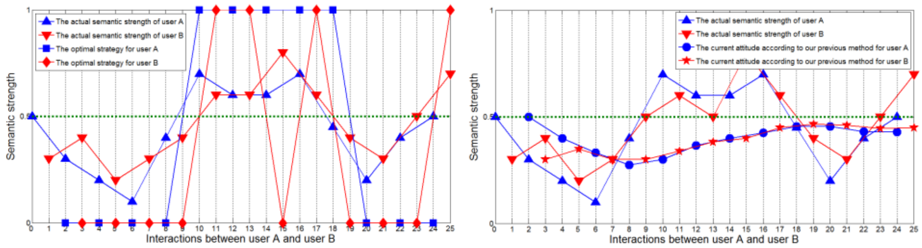


Fig. 7. The simplest discussion list which can be used to evaluate the performance of our model

We need to consider a special case in the above interaction example. As shown in Fig. 7, there is only two comments in the discussion list between users A and B. In this case, to predict the optimal strategy for user A, we assume that the pre-exsiteing attitude from user A to user B is neutral, namely, $s^{p}(A,B,0)=0.5$. The the two-comment discussion list is the simplest one which can be used to evaluate the performance of our interactive game model.



(a)The outcomes of our current attitude prediction model **(b) The outcomes of our previous method**

Fig. 8. Comparisons of the current attitude prediction model and our previous method [12]

We study a real discussion list in our Tianya data. User A first post a topic, and then user B add in to have a discussion with user A. Fig. 8 shows a comparsion of the current attitide attitude prediction model based on the recent interaction and our previous method by averaging the semantic strengths in one's previous t times interaction. As shown in Fig. 8(a), we predict one's current attitude by considering the recent interaction with his/her parter. And we use one's $t+1$th action to verify the performance of the interactive game model in his/her t th interaction. For the total twenty-four times prdictions, we have successed twenty times, the accuracy of the current attitude prediction model is 83%. In our previous work [12], we measure one's attitude to the other by simply averaging the semantic strengths in one's previous t times interactions. We also compare the outcomes of this method with the actual semantic strengths of the two users. As shown in Fig. 8(b), we have successed 13 times. The accuracy of this method is only 54%.

When we apply our current attitude prediction method to the entire Tianya data, we get an accuracy of 82%, which is very high. We also implemented the same evaluation work to our previous method. The accuracy of this method in the entire Tianya data is only 63 %; obviously, the current attitude prediction model performs much better.

4 Conclusion

Recently, online communities have become a supplemental form of communication between people. Relations on online communities often reflect a mixture of positive (friendly) and negative (antagonistic) interactions. In this paper, we develop a game theory based method to analyze the interactive patterns in online communities, which is the first in its kind. The performance of this prediction model has been evaluated by a real comment data, and the accuracy reaches 82%. Our study uncovered a number of interesting findings, some of which are related to the specific nature of online community environments.

Acknowledgments

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