DISCOVERING CRITICAL SITUATIONS IN ONLINE SOCIAL NETWORKS

A Neuro Fuzzy Approach to Alert Marketing Managers

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Abstract: More and more people are exchanging their opinions in online social networks and influencing each other. It is crucial for companies to observe opinion formation concerning their products. Thus, risks can be recognized early on and counteractive measures can be initiated by marketing managers. A neuro fuzzy approach is presented which allows the detection of critical situations in the process of opinion formation and the alerting of marketing managers. Rules for identifying critical situations are learned on the basis of the opinions of the network members, the influence of the opinion leaders and the structure of the network. The opinions and characteristics of the network are identified by text mining and social network analysis. The approach is illustrated by an exemplary application.

1 INTRODUCTION

The number of people who are engaged in online social networks is increasing steadily. Within these networks, people are passing on information and evaluations of products. By discussing with each other they influence one another's opinions and purchasing behavior. It is important for companies to monitor the development of online opinions continously in order to detect risks at an early stage and to take preventive actions. Thus, the spread of negative opinions can be stopped and the compay's image can be saved from damage.

According to diffusion theory (Rogers 2003) not only the characteristics of a product but also the social network have a great impact on the spread of opinions. Opinion leaders are in a position to influence many members of the network. The structure of the network, i.e. the relationships among the network members, determines how fast opinions disseminate.

Critical situations within social networks arise when negative opinions are on the verge of being spread and causing damage to the company's image or sales volume. The detection of critical situations is very difficult since many factors must be considered. The opinions of the network members and the power of the opinion leaders as well as the structure of the network influence the future opinion development. All of these factors must be taken into account in order to judge whether a situation is critical or non-critical. Considerable experience in the fields of online social networks and marketing is vital for evaluating situations correctly. The automation of this complex and also time-consuming task poses an immense challenge to research. A warning system should not only be able to assess situations correctly but should also be easy for marketing managers to understand so that they can apply it intuitively.

An neuro fuzzy approach is introduced which detects critical situations in the process of opinion formation by taking the overall social network into account. The opinions of the networks members are first recognized by methods coming from text mining. The opinion leaders and the network structure are then characterized by key figures coming from social network analysis. Based on this information, a fuzzy perceptron learns rules which enable the discovery of critical situations and the warning of marketing managers. These rules can be easily interpreted by marketing managers.

2 RELATED WORK

Opinion mining on the Internet has recently become a popular field of research. There are many papers

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which apply text mining to online discussions in order to reveal consumer opinions about products or product features (Kaiser 2009, Dave, Lawrence and Pennoc 2003, Pang, Lee and Vaithyanathan 2002, Popescu and Etzioni 2005). Glance et. al (2005) integrate several mining methods to enable online opinion tracking. Kim und Hovy (2007) propose a similar approach for predicting election results by analyzing predictive opinions. All of these approaches only take a static view of online opinions.

Several papers focus on the dynamic evolution of online activities. Viermetz, Skubacz, Ziegler and Seipel (2008) monitor the evolution of short term topics and long term trends. The system of Tong and Yager (2004) automatically summarizes the development of opinions in online discussions in form of linguistic statements. Huang, Liu and Wang (2007) introduce a method for detecting and tracking the evolution of online communities. Choudhury, Sundaram, John, and Seligmann (2009) extract and monitor key groups in blogs in order to study the dynamics of the whole community. These approaches deal with the dynamic evolution in the past.

Other approaches take online chatter as a basis for prediction. Gruhl, Guha, Kumar, Novak and Tomkins (2005) use online postings to predict changes and peaks in Amazon's sales. Dahr and Chang (2007) detect that user-generated content correlates with future music sales. Onishi and Manchada (2009) arrive at the conclusion that blogging activity correlates with the sales of green tea, movie tickets and cell phone contracts. All three approaches do not predict the future behavior of Internet users but only the consequences of users' online activities.

There are also studies dealing with the prediction of online behavior. Choudhury, Sundaram, John and Seligmann (2007) describe a method for predicting the communication flow in social networks. The work of Choudhury (2009) allows the modeling and forecasting of activities in online groups. However, they do not identify opinion leaders and predict opinion formation.

Welser, Gleave, Fisher and Smith (2007), Chang, Chen and Chuang (2002) as well as Gomez, Kaltenbrunner and Lopez (2008) study social networks with regard to the different roles of their members (e.g. opinion leaders). However, the content of the conversation is not taken into consideration. Bodendorf and Kaiser (2009) extract opinions by text mining and identify opinion leaders with the aid of social network analysis in order to analyze opinion formation.

None of the mentioned approaches focus on the evaluation of the situation as a whole and none of them consider all the influencing variables. Hence, former work did not enable the recognition of critical situations and the alerting of marketing managers.

3 APPROACH

The objective of the approach is to detect critical situations during opinion formation in online social networks. Situations are considered as critical if negative opinions are on the verge of spreading and harming the company's image or sales volume. In these cases, marketing managers must be warned immediately in order to take counteracting measures.

The approach comprises three succeeding mining steps. In the first step, the opinions of all network members towards a product are identified by methods coming from text mining. Opinions are distinguished as positive, negative and neutral. In the second step, the opinion leaders and the network structure which have a great impact on the spread of opinions are determined by using key figures from social network analysis. In the third step, rules for discovering critical situations during opinion formation are revealed on the basis of the overall opinion of the network, the opinion and power of the opinion leaders as well as the network structure. With the aid of a fuzzy perceptron, linguistic rules are learned which can be easily understood by marketing managers. Rules learned from past situations can be employed to recognize future critical situations and to warn marketing managers at an early stage, i.e. before the spread of negative opinions.

4 DATA COLLECTION

The presented approach is applied to the German Gaming community Gamestar.de for purposes of illustration and validation. The online platform Gamestar.de is provided by Europe's most popular magazine for computer games. Fans of computer games meet frequently on Gamestar.de to exchange opinions on many games within the discussion forum. 6596 postings submitted from Oct. 8th to Nov. 28th 2008 were extracted from threads discussing the games "Fallout 3", "Far Cry 2" and "Dead Space". For each of these three games, a sequence of time-dependent networks was generated by connecting those people with each other who have submitted postings directly before or after one another on one day.

5 IDENTIFICATION OF OPINIONS

The identification of opinions aims at detecting the attitude of each user towards a product on the basis of his/her postings. Attitudes are assigned according to their polarity to the classes “positive”, “negative” or “neutral”.

The process of opinion formation consists of two phases (Kaiser and Bodendorf 2009). First, the postings of the forum users are characterized by attributes. Second, the postings are classified according to their polarity on the basis of these attributes.

Statistical and linguistic attributes are used to describe the postings. For this reason, postings are decomposed into words. Unimportant stop words are removed. All remaining words are reduced to their word stem. The relative frequency of each word stem for each of the three classes is then calculated. Word stems which appear frequently in one class but rarely in the other two classes are chosen as attributes.

Several methods such as Hidden Marcov Models or Maximum Entropy enable the solving of classification tasks (Weiss 2005). Support Vector Machines (Cortes and Vapnik 1995) are specially suited for text classification since they are able to process numerous attributes. A lot of papers (e.g. Pang et al. 2002) have empirically demonstrated the appropriateness of Support Vector Machines for text classification. Therefore, Support Vector Machines are employed for classifying the polarity of postings based on their attributes.

In order to learn classification, training data consisting of the postings’ attributes and manually assigned polarities are required. With the aid of this training data, Support Vector Machines learn the parameters of binary classification rules. In the case of three classes, three classification rules are learned: “positive” versus “not positive”, “negative” versus “not negative” and “neutral” versus “not neutral”. The final decision to which class a posting is assigned is based on a majority vote. In the simple case of just two attributes, the classification rule can be depicted as a straight line separating the postings into two classes. Figure 1 shows a line which classifies a posting as positive due to the word stems it contains.

After classification, the average opinion of each user is determined based on all the postings he/she has submitted to the discussion forum per day

In order to validate this procedure, it was applied to the German Online Forum of Gamestar.de. 4010 postings from threads discussing the games “Dead Space”, “Fallout 3” and “Far Cry 2” were manually classified as positive, negative and neutral. The validation is executed in form of a stratified 10-fold cross-validation. The data set is divided into 10 portions so that each portion contains the same amount of postings per class. Each of the portions is used once to test the rules learned on the basis of the other nine portions. After all ten test runs, the average performance in form of precision, recall and F-measure is calculated (Weiss, Indurkhya, Zhang and Damerau 2005). While precision measures the accuracy of the classification learned, recall determines its completeness. The F-measure is calculated as the harmonic mean of precision and recall.

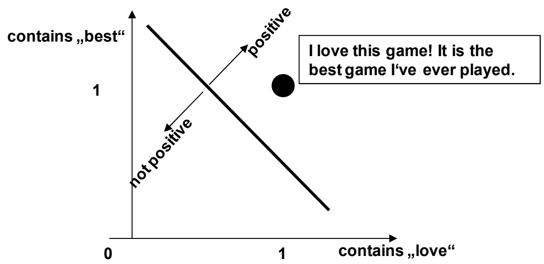

Figure 1: Classification of opinions.

Table 1 shows the results of the cross-validation. While the detection of negative and neutral opinions is very good, the detection of positive opinions is less successful. The examination of misclassification reveals that those postings with a positive introduction or positive conclusion but a neutral or negative statement in-between are often not recognized as positive. This problem can be solved by attaching more weight to the sentences at the beginning and the end of a posting.

Table 1: Results of opinion classification.

Class	Precision	Recall	F-Measure
positive	62,96%	62,52%	62,74%
negative	86,35%	86,05%	86,20%
neutral	81,65%	81,07%	81,36%

6 CHARACTERIZATION OF SOCIAL NETWORK

6.1 Opinion Leaders

Opinion leaders are persons who have great influence on other people’s opinion, attitude and behavior (Katz and Lazarsfeld 1955; Rogers 2003). While prior research in social psychology characterized opinion leaders on the basis of their personal attributes such as age and education, recent research defines opinion leaders on the basis of their social activities. Due to their central position and communicative behavior they play a leading role in opinion formation (Valente 1999). A small number of opinion leaders is sufficient to influence the opinions of many others in a network (Keller and Berry 2003). Persons are not split up in the classes “opinion leader” or “no opinion leader” but are characterized by the degree to which they affect others’ opinions (Rogers 2003).

Social Network Analysis provides three key figures for measuring the degree of opinion leadership: degree centrality, closeness centrality and betweenness centrality (Wassermann and Faust 1999, Scott 2000). The normalized values of these centrality key figures range from zero to one. While a value of one indicates maximum opinion leadership, a value of zero indicates minimum opinion leadership.

Degree centrality measures how many direct relationships a person has to other network members. It is calculated as the ratio of the number of a user’s relationships to the number of all relationships in the network. Degree centrality specifies how often a person communicates directly with other persons in the network. Persons with high degree centrality are in a position to influence their local surroundings and can be considered as local opinion leaders.

In contrast to degree centrality, closeness centrality does not only take direct but also indirect communication relationships into account. Closeness centrality characterizes how close a person is to all other persons in the network. It is calculated as the inverse sum of the distances from each user to all other users within the network. Persons with high closeness centrality are able to influence the overall network due to their short distance to all other users in the network. Therefore, they can be considered as global opinion leaders.

Betweenness centrality describes how frequently a user can be found on the shortest connecting paths between all pairs of users. This key figure is determined as the fraction of the shortest paths which pass a user to all shortest paths within the network. Since a lot of communication flows via persons with high betweenness centrality they act as intermediaries and have the power of influencing the flow of information.

6.2 Network Structure

Besides opinion leaders, the structure of the network has an impact on opinion formation. The network structure can be characterized by the key figures centralization and density coming from the social network analysis (Wassermann and Faust 1999, Scott 2000).

Centralization measures how the centralities of the network members differ from the centrality of the most central person. A strongly centralized network consists of only a few central opinion leaders and many peripheral users. In this case, the leaders’ opinion can spread easily from the center to the periphery of the network (Bodendorf and Kaiser 2009).

Density specifies the connectivity of a network. It is calculated as the fraction of the number of relationships which exist in a network and the maximum number of relationships which are possible in a network. Density indicates the frequency of communication within the network. The higher the density of a network, the more opinions can be exchanged between the network members (Bodendorf and Kaiser 2009). In a very dense network the opinion can disseminate quickly among the network members.

7 DISCOVERY OF CRITICAL SITUATIONS

7.1 Objective

The objective is to discover critical situations automatically and to alert marketing managers as soon as such a situation arises in the process of opinion formation. The classification of situations depends on many different variables such as the overall opinion, the opinions of the opinion leaders or the structure of the network.

The approach attempts to fulfill two countervailing requirements. On the one hand, marketing managers should be in a position to easily comprehend why a situation is classified as critical. Consequently, the system must be able to process linguistic rules that can be formulated by the managers due to their expertise. On the other hand, interdependencies among influencing factors are very complex and make it difficult for marketing managers to define rules for detecting critical situations. For this reason, the system must enable supervised learning of such linguistic rules from data.

7.2 Method

With regard to the two requirements mentioned above, two methods coming from the discipline of soft computing come into consideration, i.e. artificial neural networks and fuzzy systems.

Neural networks are capable of learning classification from data. However, they are a black box. There is no way of understanding the rules behind the classifications (Nauck, Klawonn and Kruse 1997). In contrast, fuzzy systems cannot learn classification from data but they can process linguistic rules that are based on fuzzy sets (Zadeh 1965). Experts formulate such linguistic rules which are then employed for classification. This enables the understanding of classification results.

In order to combine the advantages and minimize the disadvantages of neuronal networks and fuzzy systems (Nauck et al. 1997), a neuro fuzzy approach is applied in this work.

Neuro fuzzy systems have the ability of learning linguistic rules from data. There are many different neuro fuzzy approaches. Here the NEFCLASS model (NEuro Fuzzy CLASSification) is chosen. This system is capable of learning fuzzy sets and fuzzy rules. Moreover, it can also deal with manually defined rules and optimize them (Nauck et al. 1997).

The NEFCLASS model is a 3-layer fuzzy perceptron (Nauck and Kruse 1994). The input layer represents the input variables, the hidden layer the fuzzy rules and the output layer the two classes (critical situation and non-critical situation). The linguistic terms are represented by the weights between the input layer and the hidden layer (Nauck and Kruse 1995). Figure 2 illustrates the structure of a fuzzy perceptron.

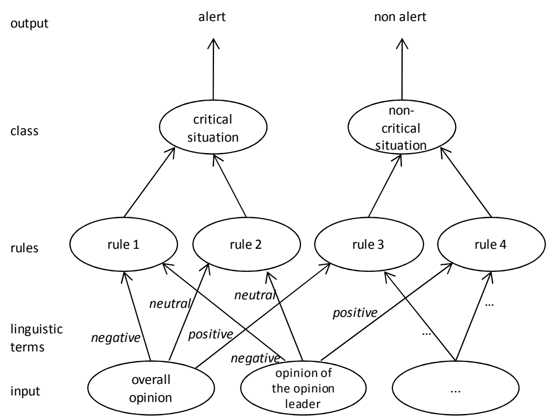

Figure 2: Structure of a fuzzy perceptron.

The fuzzy perceptron depicted in figure 2 consists of four fuzzy rules. For example, rule 1 classifies a situation as critical if the input variables overall opinion and opinion of opinion leader take the value of the linguistic term negative (see figure 3).

Rule 1

If overall opinion is negative
and opinion of opinion leader is negative
then situation is critical

Figure 3: Fuzzy rule.

Fuzzy sets specify whether and to what degree the values of the input variables belong to linguistic terms. While in classical set theory objects either belong or do not belong to a set, in fuzzy set theory objects belong to a set with a certain degree of membership. A fuzzy set is a function which assigns a degree of membership for a linguistic term to each value of the input variable (see figure 4).

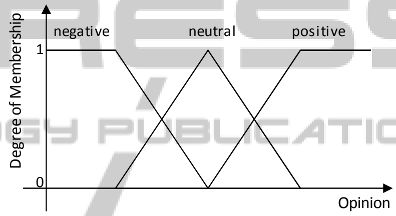

Figure 4: Fuzzy sets.

The fuzzy rules are learned from data by employing an algorithm derived from the algorithm of Wang and Mendel (Wang and Mendel 1991 & 1992, Borgelt, Klawonn, Kruse and Nauck 2003). The feature space is structured by overlapping hyperboxes which represent fuzzy rules (Nauck et al. 1997). Each hyperbox is an n-dimensional Cartesian product of n fuzzy sets (Nauck and Kruse 1997). Figure 5 shows a feature space that is structured by overlapping hyperboxes. In this case, there are two variables: opinion leadership (with the fuzzy sets *low, medium, high*) and opinion (with the fuzzy sets *negative, neutral, positive*).

The algorithm learns the fuzzy rules by running through the training data set twice. In the first run, all antecedents (*if* parts) of the rules are generated. For each pattern of the training data set, the combination of fuzzy sets which achieves the highest degree of membership is selected. In the second run, the rules are completed by determining the best consequent (*then* part) for each antecedent (*if* part). The resulting rules enable the classification of input patterns. However, there may still be some classification errors. Figure 5 (left side) exemplifies the classification of the input pattern (circles and triangles) after rule learning. One pattern is not classified (triangle) and one is misclassified (circle).

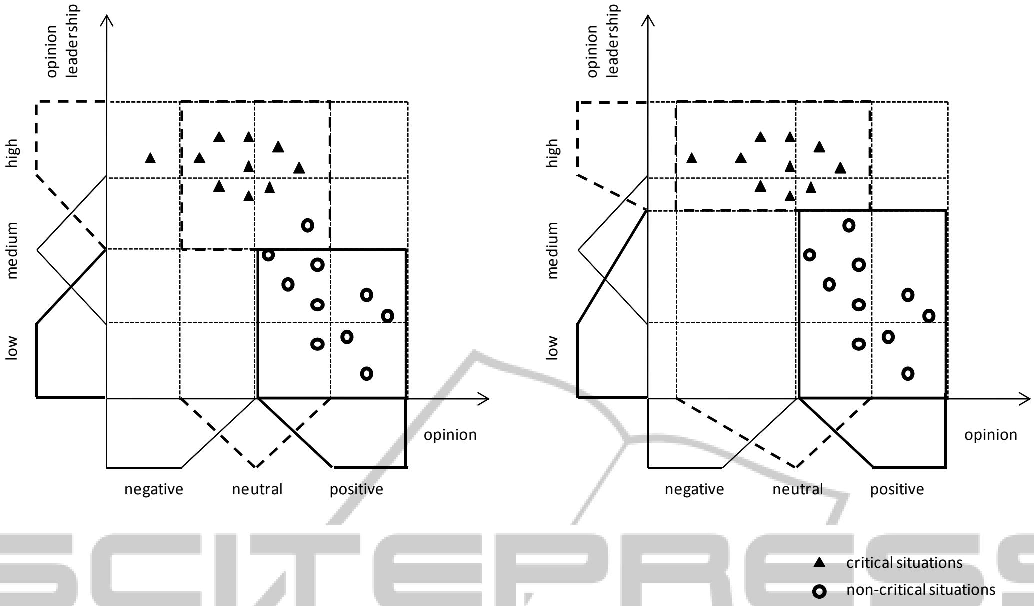

Figure 5: Classification after rule learning (left side) and after fuzzy set modification (right side).

On the basis of the detected errors the shape and the position of the fuzzy sets are modified in order to improve classification (Nauck and Kruse 1995). Figure 5 (right side) shows the classification results after the process of modification. All patterns are classified. There are no misclassifications.

After modification of the fuzzy sets, the rule base is pruned by deleting variables or whole rules. Thus, the rule base is easier to interpret and can be applied to a broader range of cases (Nauck 1996).

7.3 Application

Training Sets

Since the NEFCLASS model is based on supervised learning, the training datasets must be classified manually before learning. Each day's snapshot of the discussion network is evaluated as a critical or non-critical situation.

Figure 6 shows a situation which is not critical. The local opinion leader and the intermediary is User 25 (degree centrality 0.57, betweenness centrality 0.48). The global opinion leader is User 26 (closeness centrality 0.65). The opinion of both of them is positive. The overall opinion is neutral. The centralization, i.e. the likelihood that the opinion of the opinion leader will diffuse, is medium (0.4). The density, i.e. the speed of diffusion, is small (0.18). Consequently, this situation is classified as non-critical.

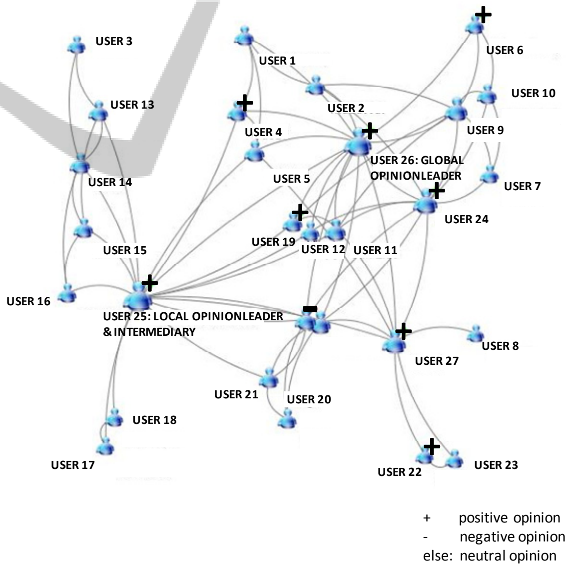

Figure 6: Non-critical situation in a network.

In contrast, the situation in figure 7 is classified as critical. Local opinion leader and intermediary is User 8. Global opinion leader is User 9. The opinion of all opinion leaders is neutral. The overall opinion is slightly negative (-0.1). The likelihood that the opinion of the opinion leader will diffuse is high (centralization 0.47). The speed of diffusion is medium (density 0.36). The situation is critical since a neutral opinion can be interpreted as disinterest.

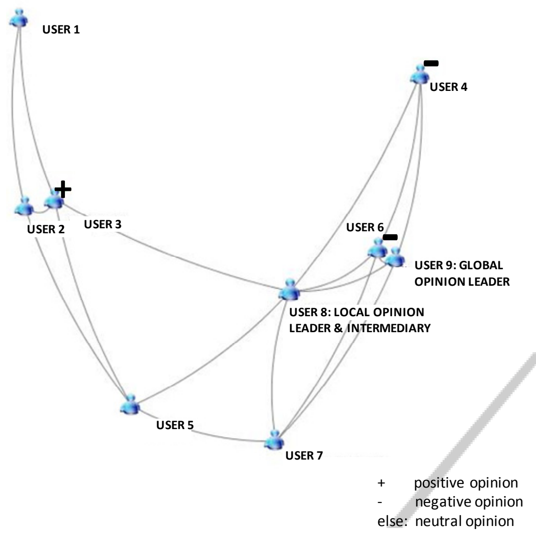

Figure 7: Critical situation in a network.

Rule Bases

Based on the training datasets, the classification rules for all three games are learned. The resulting rule bases for all three games are clear and easily interpretable. They consists of eight rules for the game "Dead Space", nine rules for the game "Fallout 3" and three rules for the game "Far Cry 2". Figure 8 shows an extraction of the rule base for the game "Dead Space".

Rule 1

If the local opinion leadership is *high*

and the opinion of the local opinion leader is *negative*

and the opinion of the global opinion leader is *negative*

and the likelihood that the opinion of an opinion leader will diffuse is *high*

and the overall opinion is *negative*

then *the situation is critical.*

Rule 2

If the opinion of the global opinion leader is *positive*

and the likelihood that the opinion of an opinion leader will diffuse is *low*

and the overall opinion is *positive*

then *the situation is not critical.*

Figure 8: Extraction of the rule base.

The first rule classifies critical situations. It states that if the overall opinion is *negative* and the opinion of the local and the global opinion leader is *negative* as well, then the marketing manager must be alerted. It is also important that local opinion leadership and centralization, i.e. likelihood of opinion diffusion, are *high*. In these situations the opinion will remain negative in the future or even become more negative. As a consequence thereof marketing manager must take actions to influence opinion formation.

The second rule classifies situations that are not critical. The opinion of the global opinion leader is *positive*. The probability that the opinion of the opinion leader will diffuse is *low*. However, this is of no disadvantage since the overall opinion is already *positive*. There is no indication that the overall opinion will become negative in the future. For this reason the marketing manager there is no need for altering the marketing manager.

Classification Results

Table 2 depicts the classification results of the three games. It shows the average rate of misclassification during validation. The best results have been achieved for the game "Fallout 3". The validated classifier has an estimated misclassification rate of 6.5%.

The classifier learned for the game "Dead Space" is also excellent. The average rate of misclassification is 9.7%. Due to the small training dataset, learning is less successful for the game "Far Cry2". There is a misclassification rate of 29.4% for the game "Far Cry 2".

Table 2: Classification results.

Game	Number of time-dependent networks	Misclassification rate
Dead Space	**56**	**9.7%**
Fallout 3	**45**	**6.5%**
Far Cry 2	**33**	**29.4 %**

8 CONCLUSIONS

The presented approach enables the detection of critical situations during opinion formation in online social networks by executing three mining steps. First, the opinions of all network members towards a product are recognized by methods coming from text mining. Second, the opinion leaders and the structure of the network are determined by key figures coming from social network analysis. Third, critical situations during opinion formation are spotted by a fuzzy perceptron on the basis of the opinions of the network members, the influence of the opinion leaders as well as the structure of the network. Choosing a neuro fuzzy approach allows the learning of linguistic rules which can be easily interpreted by marketing managers. These rules are learned from past situations and can be employed to judge future situations.

There are a lot of advantages in discovering critical situations. Being alerted at an early stage, marketing managers can influence the process of opinion formation. For instance, they can address opinion leaders who have a negative opinion and ask their advice about product improvements. This action might not only reveal valuable information for product development but might also lead to a change in the leaders' opinions as they have the impression that their complaint is being taken seriously. All in all, this approach attempts to improve a company's image and to increase its sales volume.

Scheduled work is to implement a decision support system that not only identifies critical situations but also generates recommendations on appropriate actions for marketing mangers. For example, the system should advise marketing managers how to communicate with network members in critical situations.

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