Fake reviews detection under belief function framework

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Abstract. Online reviews have become one of the most important sources of customers opinions. These reviews influence potential purchasers to make or reverse decisions. Unfortunately, the existence of profit and publicity has emerged fake reviews to promote or demote some target products. Furthermore, reviews are generally imprecise and uncertain. So, it is a difficult task to uncover fake reviews from the genuine ones. In this paper, we propose a fake reviews detection method using the belief function theory. This method deals with the uncertainty in the given rating reviews and takes into account the similarity with other provided votes to detect misleading. We propose numerical examples to intuitively evaluate our method. Then, to prove its performance, we conducted on a real database. Experimentation shows that the proposed method is a valuable solution for the fake reviews detection problem.

Keywords: Online opinions, Fake reviews, Uncertainty, Belief function theory.

1 Introduction

During the last years, we notice the emergence of the opinions sharing websites such as Amazon.com, Tripadvisor.com, Yelp.com, PriceGrabber.com, Shopzilla.com and Resellerratings.com, which allow people to share their experiences, feelings, attitudes regarding products, services, business and even political issues. Such opinions, straightforwardly influence potential future customers and companies to make or reserve decisions.
Consequently, the increasing of positive reviews number will transform their readers to new customers which will provide significant financial gains. Similarly, negative reviews often cause financial losses.
Due to the reviews' dominance power, spammers create fake reviews to deteriorate the online reviews systems and confuse the consumers. This spam review does not reflect the real opinion reviewer's and it is intended for misleading reviewers' readers. It may be supportive in order to over qualify a product or a service or destructive to damage the e-reputation of competitors companies.

Therefore, it is crucial to detect fake reviews in order to protect e-commerce form fraudsters' activities, to ensure customers confidence and to maintain companies' fair competition. As a consequence, spam reviews detection became one of the most challenging problems. Researchers have developed various spam detection techniques in which the major task is distinguishing between fake reviews and truthful ones. A largest number of methods and techniques is proposed to detect spam reviews. Most of these works tried to distinguish between fake and true opinions across the linguistic aspects and feeling [3], as well as the style of writing [2, 8], and readability and subjectivity [13]. Some researchers try to catch the group spammers cause of their ability to manipulate the readers' desires, beliefs and consciousness for both product and service. In [12], the authors have studied this problem by defining a set of eight indicators that try to detect behavior of the group members such as time and rating deviation. Other studies [11] proposed the score candidate groups using the relationship between groups, individuals and products. Other techniques have focused on spammer detection. Most of them are graph based approaches [1, 6, 19] with tree types of nodes namely: review, reviewer and stores. The deviation from overall ratings was used as features in [14, 16, 20] and all these studies have bring a significant results. An algorithm to detect burst patterns in reviews was proposed in [7]. It generated five new spammer behavior features as indicators to used them in review spammer detection. In addition, an other method, proposed in [9], used three detection metrics (Context similarity authors' activeness, Authors' rating behavior) to score each review and detect spam ones.
Up to our knowledge, no one of the previous works is able to handle uncertainty in reviewers' votes. In fact, the fake reviews detection is an uncertain problem and involves imperfection concerning given reviews. In this context, we propose a novel method, the belief fake reviews detection (BFRD), based on the belief function theory. Indeed, this theory is able to handle uncertainty and allows to deal with partial and total ignorance. It can manipulate various pieces of information from different sources and also take into account their reliabilities through the discounting operation. Moreover, the similarity between the difference given reviews can be taken into account through the distances proposed under belief function framework and especially without forgetting its powerful on decision making under uncertainty. In addition, our proposed method takes into account the case where we have a lack of information and deals with only the overall rating reviews.
The remainder of this paper is structured as follows: In Section 2, we present the belief function theory concepts. Then in Section 3, our proposed method named BFRD, is detailed. Experimentation will be proven through the use of the numerical examples in Section 4. Finally, we conclude in Section 5.

2 Belief Function Theory

The belief function theory was introduced by Shafer [15] as a model to represent beliefs. It is considered as an efficient tool able to deal with uncertainty and to manage several types of imperfection. Various interpretations have been proposed from this theory, including the Transferable belief model (TBM) [17] that we adopt in our work. In this section, we elucidate the crucial basic belief concepts, the discounting operation, some combination rules and the decision process.

2.1 Basic concepts

The universe of discourse Ω is a finite and exhaustive set of different events associated to a given problem. Its power set 2^{Ω} contains all possible hypotheses that formed union of events, and the empty set which represents the conflict, defined by: $2^{\Omega} = \{A : A \subseteq \Omega\}$. A basic belief assignment (*bba*) or a belief mass defined as a function from 2^{Ω} to $[0,1]$ such that: $\sum_{A\subseteq\Omega} m^{\Omega}(A) = 1$. Each subset A of Ω, having a strictly positive mass $m^{\Omega}(A) > 0$, is considered as the focal element of the *bba*. In order to express several types of imperfection, some special *bbas* were defined:

- A certain *bba* is defined as follows: $m^{\Omega}(\{\omega_i\}) = 1$ and $\omega_i \in \Omega$.
- A vacuous *bba* is defined as follows: $m^{\Omega}(\Omega) = 1$ $m^{\Omega}(A) = 0$ $\forall A \neq \Omega$. This function models the state of the total ignorance.
- A categorical *bba* is defined as follows: $m^{\Omega}(A) = 1$ $\forall A \subset \Omega$ and $m^{\Omega}(B) = 0$ $\forall B \subseteq \Omega$ $B \neq A$. This *bba* has a unique focal element A.
- A simple support function is defined as follows:

$$m^{\Omega}(X) = \begin{cases} \omega & \text{if} \quad X = \Omega \\ 1-\omega & \text{if} \quad X = A \quad \forall A \subset \Omega \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

  where A is the focal element and $\omega \in [0,1]$.

2.2 Discounting operation

The discounting operation established by [15] allows us to weaken the masses by the *discount rate* $\alpha \in [0,1]$ such that $(1-\alpha)$ is the degree of reliability of a source.
Accordingly, the discounted *bba*, noted m^{α}, becomes:

$$\begin{cases} {}^{\alpha}m^{\Omega}(A) = (1-\alpha)m(A) & \forall A \subset \Omega, \\ {}^{\alpha}m^{\Omega}(\Omega) = \alpha + (1-\alpha)m(\Omega). \end{cases} \tag{2}$$

2.3 Combination Rules

Let m_1^{Ω} and m_2^{Ω} two different *bbas* defined on the same frame of discernment Ω providing by two distinct and cognitively independent reliable sources.
There are several combination rules proposed in the belief function framework, each rule has its specificities and its characteristics. Then, we will present some of the most used ones.

1. *Conjunctive rule* (*CRC*)**:** Introduced by Smets [18], it allows to combine two *bbas* induced by distinct and reliable sources of information. It is denoted by $\textcircled{\cap}$ and defined as:
$$m_1^\Omega \textcircled{\cap} m_2^\Omega(A) = \sum_{B \cup C = A} m_1^\Omega(B) m_2^\Omega(C) \tag{3}$$
The mass assigned to the empty set quantifies the degree of conflict between the two *bbas*.
2. *Dempster's rule of combination*: It is the normalized version of the conjunctive rule where it does not support the existence of a mass on the empty set [4]. It is denoted by $\oplus$ and defined as:
$$m_1^\Omega \oplus m_2^\Omega(A) = \begin{cases} \frac{m_1^\Omega \textcircled{\cap} m_2^\Omega(A)}{1 - m_1^\Omega \textcircled{\cap} m_2^\Omega(\emptyset)} & \text{if} A \neq \emptyset, \forall A \subseteq \Omega, \\ 0 & otherwise. \end{cases} \tag{4}$$
3. *The combination with adapted conflict rule* (*CWAC*)**:** This combination [5] act as the conjunctive rule when the *bbas* are antonym (it keeps the conflict) and as the Dempster rule when the *bbas* are similar.
They use the notion of dissimilarity that is obtained through a distance measure, to ensure this adaptation between all sources. The CWAC is formulated as follows:
$$m^\Omega_{\textcircled{\leftrightarrow}}(A) = (\textcircled{\leftrightarrow} m_i^\Omega)(A) = D_{max} m^\Omega_{\textcircled{\cap}}(A) + (1 - D_{max}) m^\Omega_{\oplus}(A) \tag{5}$$
where D_{max} represents the maximal value of all the distances, it can be used to find out if at least one of the sources is opposite to the others and thus it may be defined by:
$$D_{max} = max[d(m_i^\Omega, m_j^\Omega)], \tag{6}$$
where $i \in [1, M]$, $j \in [1, M]$, M is the total number of mass functions and $d(m_i^\Omega, m_j^\Omega)$ is the distance measure proposed by Jousselme [10]:
$$d(m_1^\Omega, m_2^\Omega) = \sqrt{\frac{1}{2}(m_1^\Omega - m_2^\Omega)^t D (m_1^\Omega - m_2^\Omega)}, \tag{7}$$
where D is the Jaccard index defined by:
$$D(E, F) = \begin{cases} 0 & \text{if} \quad E = F = \emptyset, \\ \frac{|E \cap F|}{|E \cup F|} & \forall E, F \in 2^\Omega \end{cases} \tag{8}$$

2.4 Decision Making

The decision making step chooses the most suitable hypothesis for a given problem. The Transferable Belief Model (TBM), proposed by [18], is composed by both the credal level where beliefs are defined by *bbas* then combined, and the pignistic level where *bbas* are transformed into pignistic probabilities denoted by $BetP$ and defined as follows:
$$BetP(B) = \sum_{A \subseteq \Omega} \frac{|A \cap B|}{|A|} \frac{m^\Omega(A)}{(1 - m^\Omega(\emptyset))} \quad \forall\ B \in \Omega \tag{9}$$

3 The belief fake reviews detection (BFRD)

The proposed method, in this paper, deals with fake reviews detection using the belief function tools. In order to distinguish between fake and genuine reviews, this method only requires the overall rating as an input. Given a dataset of N votes that have different values between 1 and 5 stars (respectively poor, below average, average, good and excellent), each vote V_i is associated to a reviewer denoted R_i where i is the *id* of the corresponding one. Our method follows four main steps detailed in-depth.

3.1 Modeling reviewer's vote by mass functions

As we adopt the belief function theory in order to model conveniently imperfections in votes, each vote V_i will be transformed into a mass function (i.e. bba) m_i^{Ω} with Ω =$\{1, 2, 3, 4, 5\}$ where one of the elements in Ω represents the stars' number given by each reviewer R_i.
We think that the reviewer is either a spammer or a real customer gives an uncertain vote. We propose to model this uncertainty by considering the vote, the vote-1 and the vote+1 for each given overall rating review. In the upper extreme case (i.e. $V_i = 5$), we model the vote and the vote-1 and in the lower one (i.e. $V_i = 1$) we model the vote and the vote+1.
We transform each vote value V_i given by the reviewer R_i into *bbas* defined as follows:

$$m_{ik}^{\Omega}(\{k\}) = 1$$

where $k = \begin{cases} V_i \\ V_i + 1 \\ V_i - 1 \end{cases}$. In the upper extreme case, $k = \begin{cases} V_i \\ V_i - 1 \end{cases}$ and in the lower extreme case, $k = \begin{cases} V_i \\ V_i + 1 \end{cases}$.

Example 1. Let us consider the case of five reviewers given an overall rating review for an hotel detailed in Table 1.
For R_1: $m_{14}^{\Omega}(\{4\}) = 1$; $m_{15}^{\Omega}(\{5\}) = 1$; $m_{13}^{\Omega}(\{3\}) = 1$.
For R_3: $m_{35}^{\Omega}(\{5\}) = 1$; $m_{34}^{\Omega}(\{4\}) = 1$. For R_5: $m_{51}^{\Omega}(\{1\}) = 1$; $m_{52}^{\Omega}(\{2\}) = 1$.

We propose to model the reliability degree of the reviewer R_i by $(1 - \alpha_i)$ where α_i is its discounting factor. Its value is between $[0, 1]$, if $\alpha_i = 0$ the reviewer is totally reliable and if $\alpha_i = 1$, it means that the reviewer is totally unreliable and it will not be taken into account. We calculate α_i as follows:

$$\alpha_i = \frac{\text{Number of votes different from the current vote of } R_i}{\text{Total votes' number}} \tag{10}$$

So, each vote transformed into mass functions is weakened by its relative reliability degree $(1 - \alpha_i)$ using the discounting operation and consequently changed

Table 1. Hotel reviews

Reviewer	Vote
R_1	4 stars
R_2	4 stars
R_3	5 stars
R_4	3 stars
R_5	1 star

into simple support functions. Thus, the reliability of the reviewer will be taken into consideration.

Example 2. We continue with the previous Example 1, we calculate the reliability factor for R_1: $\alpha_1 = \frac{3}{5} = 0.6$.
After the discounting operation the *bbas* are transformed into a mass functions as follows: ${}^{\alpha_1}m^{\Omega}_{14}(\{4\}) = (1-0.6)*1 = 0.4$; ${}^{\alpha_1}m^{\Omega}_{14}(\{\Omega\}) = 0.6+(1-0.6)*0 = 0.6$. ${}^{\alpha_1}m^{\Omega}_{15}(\{5\}) = 0.4$; ${}^{\alpha_1}m^{\Omega}_{15}(\{\Omega\}) = 0.6$. ${}^{\alpha_1}m^{\Omega}_{13}(\{3\}) = 0.4$; ${}^{\alpha_1}m^{\Omega}_{13}(\{\Omega\}) = 0.6$.

In addition, we propose to model the distance between the i^{th} given vote value denoted by V_i and its corresponding modeled values (vote, vote+1 and vote-1) denoted by k and represented by m_{ik}, in order to not consider them in the same way, by $(1 - \beta_{ik})$ where β_{ik} is its discounting factor. Its value is between $[0, 1]$, if $\beta_{ik} = 0$ it means that the vote represents the current vote value and if $\beta_{ik} = 1$ it means that the vote is so far from the current vote value. The discounting factor β_{ik} is calculated as follows:

$$\beta_{ik} = \frac{|V_i - k|}{\text{The maximum vote value}} \tag{11}$$

Then, each simple support function associated to each vote given by a review is weakened by its relative reliability degree $(1 - \beta_{ik})$ using the discounting operation.

Example 3. Let us consider the same Example 1, we calculate the discount factor β for the R_1: $\beta_{14} = \frac{|4-4|}{5} = 0$; $\beta_{15} = \frac{|4-5|}{5} = 0.2$; $\beta_{13} = \frac{|4-3|}{5} = 0.2$.
After the second discounting operation, the *bbas* are transformed as follows:
${}^{\alpha_1\beta_{14}}m^{\Omega}_{14}(\{4\}) = 0.4$; ${}^{\alpha_1\beta_{14}}m^{\Omega}_{14}(\{\Omega\}) = 0.6$.
${}^{\alpha_1\beta_{15}}m^{\Omega}_{15}(\{5\}) = 0.32$; ${}^{\alpha_1\beta_{15}}m^{\Omega}_{15}(\{\Omega\}) = 0.68$.
${}^{\alpha_1\beta_{13}}m^{\Omega}_{13}(\{3\}) = 0.32$; ${}^{\alpha_1\beta_{13}}m^{\Omega}_{13}(\{\Omega\}) = 0.68$

Finally, we aggregate each three discounted *bbas* (two in the extreme cases) representing each given vote using the Dempster rule (Eq.4) in order to represent each given vote by one *bba* containing four focal elements (three in the extreme cases).

Example 4. After aggregating the discounted votes corresponding to R_1 calculated in Example 3 using the Dempster rule, we found:
$m_1^\Omega = {}^{\alpha_1\beta_{14}}m_{14}^\Omega \oplus {}^{\alpha_1\beta_{13}}m_{13}^\Omega \oplus {}^{\alpha_1\beta_{15}}m_{15}^\Omega$
$m_1^\Omega(\{4\}) = 0.255$; $m_1^\Omega(\{5\}) = 0.180$; $m_1^\Omega(\{3\}) = 0.180$; $m_1^\Omega(\Omega) = 0.385$.
Then this *bba* will represent the vote (4 stars) given by R_1.

3.2 Distance between the current reviewer's vote and all the other votes' aggregation

In order to evaluate the vote provided by each reviewer, we compared it to all other reviewers' vote as follows:
For each reviewer, we aggregate all the other reviewers' votes represented by *bbas* using the CWAC combination rule (Eq.5) chosen, because it can cope with the conflict in different votes. The output of this combination is one *bba* m_{ci}^Ω, which represents the whole reviewers' votes except the current one as follows:
$m_{ci}^\Omega = m_1^\Omega \circledast m_2^\Omega \circledast \ldots \circledast m_{i-1}^\Omega \circledast m_{i+1}^\Omega \circledast \ldots \circledast m_N^\Omega$.
Then, we calculate the distance $d(m_i^\Omega, m_{ci}^\Omega)$ using the distance of Jousselme (Eq.7), in order to measure the similarity between each review's vote and all others.

Example 5. We continue with the previous Example 4 where the current vote corresponds to the first reviewer R_1, so we aggregate all the reviewers' votes except the first one: $m_{c1}^\Omega = m_2^\Omega \circledast m_3^\Omega \circledast m_4^\Omega \circledast m_5^\Omega$.
$m_{c1}^\Omega(\emptyset) = 0.16$; $m_{c1}^\Omega(\{1\}) = 0.04$; $m_{c1}^\Omega(\{2\}) = 0.25$; $m_{c1}^\Omega(\{3\}) = 0.15$;
$m_{c1}^\Omega(\{4\}) = 0.25$; $m_{c1}^\Omega(\{5\}) = 0.15$.
Then, we apply the Jousselme distance between the first reviewer's vote and all the other ones, we found: $d(m_1^\Omega, m_{c1}^\Omega) = 0.155$.

3.3 Construction of a new *bba* modeling the vote into fake or not fake

The distance measured in the previous step represents the degree of compatibility between the vote and all the other ones' which means that more the distance value decreases more the vote is reliable. So, we propose to transform each distance into a new *bba* with $\Theta = \{f, \bar{f}\}$ f= fake and $\bar{f}$= not fake as the following equation:

$$\begin{cases} m^\Theta(\{f\}) = \gamma * \frac{1}{1+e^{-a.ds+\frac{a}{2}}} \\ m^\Theta(\{\bar{f}\}) = \gamma * (1 - \frac{1}{1+e^{-a.ds+\frac{a}{2}}}) \\ m^\Theta(\Theta) = 1 - \gamma \end{cases} \tag{12}$$

with $ds = d(m_i^\Omega, m_{ci}^\Omega)$, $a = 10$ and $\gamma = \frac{\text{The standard deviation of all votes}}{\text{The maximum value of the standard deviation}}$

Example 6. We transform the Jousselme distance $d(m_1^\Omega, m_{c1}^\Omega)$ calculated in the previous Example 5 into a new *bba* with $\Theta = \{f, \bar{f}\}$, we found:
$m^\Theta(\{f\}) = 0.018$; $m^\Theta(\{\bar{f}\}) = 0.562$; $m^\Theta(\Omega) = 0.42$.

3.4 Decision making

The decision process is made in this final step and assured by the pignistic probability $BetP$ (Eq.10). The $BetP$ with the greater value is considered as the final decision.

Example 7. After applying the pignistic probability on the *bba* calculated in the previous Example 6, we found: $BetP(\{f\}) = 0.227$; $BetP(\{\bar{f}\}) = 0.773$.
Thus, we assume that the vote given by the first reviewer is a genuine one.

4 Experimentation and results

In the fake reviews detection, the evaluation is one of the most challenging problems considering the unavailability of the labeled dataset because it is not obvious to distinguish between the fake and the real reviews, even with the knowledge of spammers and no spammers. In this paper, we propose to use the numerical examples to intuitively validate our method.

Figure 1 represents the obtained results in four different examples that are

Table 2. The numerical examples' results

The numerical examples	Opinion		Fake rating stars	Not fake rating stars
	Rating Stars	Number of reviewers		
Example 1	5* 4* 3* 2* 1*	5 5 5 5 5	-	5*, 4*, 3*, 2* and 1*
Example 2	5* 4*	5 5	-	5* and 4*
Example 3	5* 1*	5 5	-	5* and 1*
Example 4	4* 5* 3* 2* 1*	4 2 2 1 1	2* and 1*	4*, 5* and 3*

detailed in Table 2, where the reviewers judge a hotel by giving rating stars (denoted by * in Table 2). We deal with one standard case and three particular ones, where the given reviews represent five and two majority class rating stars. We can assume that our method provides logical results with different cases.
Then, in order to test our BFRD performance, we used a real database extracted from Tripadvisor. The dataset consists of a 1550 reviewers who express their opinion on "Melia Caribe Tropical hotel" by writing reviews, giving an overall,

and vote other criteria. Our proposed method detects 967 fake reviews and 583 genuine ones.

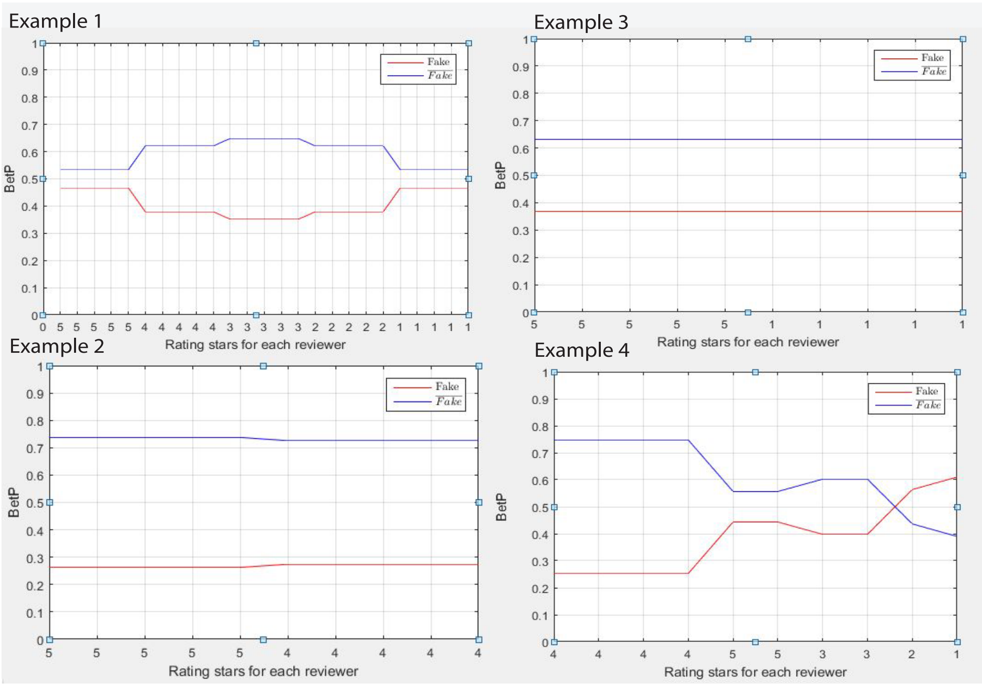

Fig. 1. The numerical examples' results

5 Conclusion

In this paper, we addressed the fake reviews detection problem in an uncertain context through the belief function tools. We proposed to handle uncertainty in the given rating reviews and to evaluate them through their compatibility with all others. In fact, our new method shows effectiveness in distinguishing between the fraudulent reviews and the honest ones. Moreover, this approach can be applied in several fields such as e-commerce and e-business. As future work, we will integrate some other notions like reviewers' trustiness.

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