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A New Approach to Compute a Realistic Credibility Rank for Reviewers Using Fuzzy Inference

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Abstract— **Online product review websites as one of the examples of Web 2.0 websites allow users share their ideas and opinions about various products and services. Although online reviews as a user-generated content can be considered as an invaluable source of information for both consumers and firms, these reviews vary greatly in term of quality and credibility. To tackle the problem of low quality reviews, we address reviewer credibility and propose a novel and feasible framework for ranking reviewers in terms of credibility. The proposed framework exploits four kinds of features including social network, profile, engagement and knowledge to quantify reviewer credibility dimensions and utilize a fuzzy inference system to calculate credibility scores of reviewers in a cognitive approach. To illustrate an application of the proposed method, we conduct an experimental study using real data gathered from Epinions. The proposed framework can support marketing departments in identifying the most credible reviewers.**

Keywords: Social Web; Online Reviews; Reviewer Credibility; Social Network; Shannon Entropy; Fuzzy Inference Systems.

I. INTRODUCTION

With the advent of web 2.0 [1] many social web applications such as online product review communities are being developed on which users can share their ideas and opinions about various products and services. Websites such as Epinions.com, Yelp.com, and Ciao.com have become a platform on which reviewers can write reviews about particular products. Online reviews produced in online communities can be considered as an invaluable source of information for both consumers and firms. The contents can be utilized by consumers to make informed purchase decisions. In addition, firms and especially marketing departments can retrieve online reviews to perform analysis about their customers' attitude and sentiments regarding their products and services. Particularly, firms can employ text-mining tools and techniques to extract opinions of users about their products and services. So far, many research addressed the problem of opinion mining from customer reviews (e.g. [2-9]).

In an online product review website, many reviewers with different levels of credibility can easily post reviews about various types of products. Consequently, online reviews vary greatly in terms of quality [10]. In other words, due to the lack of a comprehensive mechanism to validate online reviews, some low quality, uninformative online reviews may be produced [11]. To tackle review quality problem, we address reviewer credibility

The proposed framework can help consumers in finding credible reviewers and reviews and there by facilitating, purchase decisions. Besides, companies can employ the framework to gain insights about customers' opinions and sentiments regarding their products and services in an efficient and effective manner. The rest of the paper is organized as follows. Section 2 describes background and reviews related works on social web and source credibility. In section 3, we describe the proposed framework for reviewer ranking in terms of credibility. Section 4 demonstrates an implementation of the proposed framework using real data. In section 5, we discuss about the performance of the proposed method. Section 6 concludes the paper

II. RELATED WORKS

A. *Social Web*

Social web application can be categorized into three main types: those that focus on products, those that focus on contents, and those that focus on activity [16]. In social web applications, users interact with each other and generate contents by sharing with friends their knowledge and experiences about products, paid services, firms, etc. Product review sharing websites (e.g. Epinions.com, Ciao.com) as example of social web applications allow users to share reviews about various products. In addition, these platforms allow users to explicitly maintain a trust and distrust list and thereby constituting Web of Trust (WOT) among themselves, (i.e. a network of pair-wise trust relationships) [17]. The generated contents often circulate through social relations and influence other individuals' decisions regarding their future decisions [17]. Both users' social networks and generated contents can be exploited by firms to conduct various marketing programs such as utilizing users' reviews to understand users' sentiments about their products and services, and identifying influencer for word-of-mouth marketing [18].

B. *Source Credibility*

Credibility of online reviews is important since consumers and marketing departments explore them to gain insight about a certain products or services. Source credibility defined by Hovland, et al. (as cited in [11]) as expertise and trustworthiness. Several different dimensions for source credibility have been identified in the later studies; however, the initial two dimensions, expertise and trustworthiness are still the focal dimensions [11].

Much of the research in the credibility context has focused on discovering factors affecting credibility of source without performing a quantitative evaluation [11]. However, there exist some researches addressed the problem of measuring source credibility. In [11] a method to quantify the credibility of reviewers in Tripadvisor using two novel indexes: Impact index and exposure-impact index was developed. In [12] an algorithm called CredRank algorithm to measure users' credibility based on their behavior in social media. In this study, we aim at measuring reviewer credibility based on the two principal source credibility dimensions including trustworthiness and expertise. In this paper, a new method for calculating credibility of reviewers using fuzzy inference based system is proposed. To illustrate an application of the proposed method, we conduct an experimental study using real data crawled from Epinions.

III. RESEARCH FRAMEWORK FOR REVIEWER RANKING

The framework of this study for reviewer ranking is illustrated in Fig.1. As depicted in the figure, the proposed framework consists of five important phases including discovering source credibility dimensions, crawling related data, constructing the required features, computing features weights using Shannon entropy, designing the fuzzy inference system for calculating credibility and finally ranking the reviewers in terms of credibility

IV. IMPLEMENTATION OF THE PROPOSED FRAMEWORK

In this section, we implement the framework using data crawled and provide an in-depth description for each phase.

A. *Analyzing source credibility problem of online reviews*

Credibility dimensions are divided into three types: Source credibility, message credibility and medium credibility [11, 19]. Credibility assessment of source and message are fundamentally and positively interdependent [11]. Information quality and source credibility are predictors of information usefulness [19]. Credibility is a principal attribute of information quality [19]. Considering this insight and in line with [11], in this paper, we focus on quantifying source credibility in product review websites to identify credible reviews. In a product review website, the review, reviewer and website can be considered as the message, source and medium, respectively.

As pointed out in the related works, trustworthiness and expertise are the focal dimensions of source credibility [11]. Thus, to measure the source credibility of reviewers, it is essential to collect the data relevant to these dimensions. Therefore, in order to quantify reviewers' credibility, we consider reviewers' trustworthiness and expertise.

B. *Crawling Data from web*

The second critical phase is the crawling step in which the required data were gathered from the web. As a case study, we selected the Epinions.com, which is a well-known product review web site. Epinions is a large community network that enables users to share their knowledge and experiences about products and services. In epinions.com, users can write reviews of products and services of various categories, for instance electronic, Hardware and software, home and garden and so on. In addition, users can rate others' reviews with numerical rating ([1, 5]). The generated reviews can help users to make appropriate decisions in the process of purchasing a product or services. Each Epinions user can explicitly express trust or distrust relationships to other users. Therefore, a web of trust (WOT) is established through a set of trust relationships.

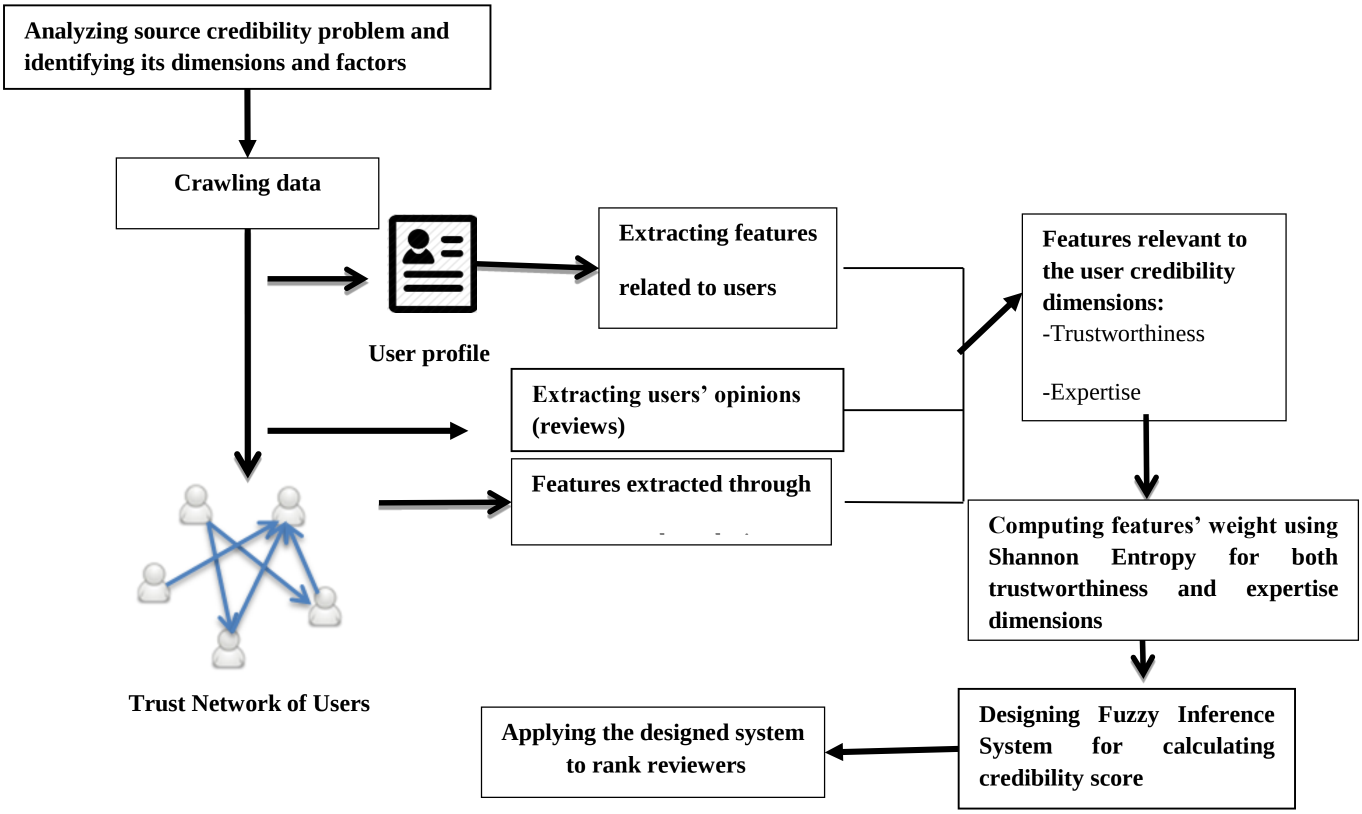

Fig.1. Research framework

In this study, we interested in collecting data of reviewers from electronic category. In order to crawl users' network, we started from the top reviewer in the product category "Electronics" and followed both the top reviewer's trusts and trusted by links to find other users. We used breadth first search strategy to crawl users' network. The data crawled fall into three categories: (1) data of trust network among users (WOT), (2) data of user profile, for example, number of past reviews, number of user visits, length of activity, number of personal information items disclosed;(3) data about the reviews including review written date, title, category, product rating, and helpfulness rating during a period of 1-year. The statistics of crawled data is given in Table 1.

Table 1: statistics of data crawled

Description	Number of
#Users	13419
# Trust relations	475574
# Reviews in one year	15312

The crawled data should be preprocessed before entering to the next phase. According to the crawl results, certain amount of users had not write reviews during the 1-year periods. Therefore, these users were filtered out. Besides, some users did not contribute in electronic categories so we eliminated them from our data. After preprocessing, the number of active reviewers was reduced to 227.

C. Deriving and constructing features corresponding to the trustworthiness and expertise

This phase is a significant phase in which the required features were extracted and derived from the data based on the two chief dimensions of source credibility including trustworthiness and expertise. The extracted features are shown in Fig. 2. According to what mentioned in the related works, source trustworthiness and expertise are the two primary determinants of source credibility [11, 20]. In the following, we portray the derived features corresponding to the each of these two dimensions corresponding to the each of these two dimensions.

1) Trustworthiness

Trustworthiness is defined as the extent to which an information source is perceived as providing information that reflects the source's real opinions and attitudes regarding something [11, 21]. Trustworthiness is usually described by terms such as well intentioned, truthful and unbiased [11]. Based on the data crawled from the website, several features relevant to the trustworthiness dimension can be derived. As pointed out before, in the web site used as a case study, users can constitute trust network, which is known as Web of trust in the literature by explicitly expressing whom they trust. Therefore, web of trust can be a strong source for inferring the extent of a user's trustworthiness.

To derive and compute features indicating a user's trustworthiness from his/her web of trust, we employed social network analysis to compute users' importance in the trust network. Although, many centrality measures have been devised to measure the importance and popularity of a node in a social network, in-degree (the number of incoming ties) [22], PageRank [22, 23] are two effective and suitable algorithms to calculate importance of nodes in a social network. In this paper, we calculate these two measures. More details about the social network based features are demonstrated in Fig. 2.

According to the Google website, "the heart of Google software is PageRank". In short, PageRank thesis is that a webpage is important if it is pointed to by other important pages [24]. Today Google's algorithms rely on more than 200 unique signals or "clues" that make it possible to guess what you might really be looking for. These signals include things like the terms on websites, the freshness of content, your region and PageRank. During the processing of a query, Google's search algorithm combined pre-computed PageRank scores with text matching scores to obtain an overall ranking score for each webpage.

To calculate PageRank scores, web graph is utilized. PageRank can be calculated using a simple iterative algorithm, and corresponds to the principal eigenvector of the normalized link matrix of the web [25]. In this paper, we utilize the idea of PageRank in order to calculate the popularity of each reviewer in his/her trust network. Trust network is a directed graph whose nodes represent entities (reviewers) and edges represent trust relationships between reviewers.

Two features relevant to the trustworthiness dimension including User Visits, and Number of Personal Information derived from profile data of users (as seen from Fig. 2 and Table 2). The reason for including User Visits feature as a representative of trustworthiness of a reviewer is that the high number of User Visits indicates that much more people have visited and read the user's reviews which in turn reflecting that the user has written more reliable and truthful reviews. In addition, the feature, Number of Personal Information, is selected as a representative for the source credibility and especially for the trustworthiness. According to [26, 27], revealing personal identity information by reviewer has positive effect on the perceived credibility of online reviews and can facilitate the evaluation of the aspects of the reviewers. Recency, which is defined as the time elapsed since the last review was written by a reviewer, may be a cue for active participation or activeness of a reviewer which in turn indicating a reviewer trustworthiness. To derive the recency feature, we adopt the principle of RFM Analysis [28]. All of the features derived to compute the trustworthiness are described in Table 2.

2) Expertise

Expertise is the degree to which an information source is perceived as being able to know truth or to present valid information [11, 21]. It is often expressed by terms such as experienced, knowledgeable, and competent [11]. Expertise directly relates to knowledge about the goods or services, and increases as related experiences increase [13]. Therefore, there is a close relation between expertise, knowledge and experience. In [13], the authors used the number of destinations visited to measure expertise of a reviewer in TripAdvisor[1].

In this study, we computed the experience feature as the length of participation of the reviewer in the web site. In addition, some features from engagement features class indicating the past activity and level of contribution of reviewer including, number of reviews written by user, in all category and in specific domain and the number of reviews written by user since membership date were employed to quantify the expertise of reviewers. Fig. 2 and shows the features utilized to quantify the expertise dimension.

As mentioned before, expertise closely relate to knowledge, so here we compute knowledge score of reviewers based on the number of reviews written and overall satisfaction on reviews which is calculated as the average of other users ratings on review written by the reviewer. Since each reviewer usually writes reviews on products and services from various categories, we estimate general knowledge and domain specific knowledge scores for each reviewer. Furthermore, we consider the number of categories on which a reviewer wrote reviews as the extent of knowledge of the reviewer. The higher the number of categories implies the wider the range of expertise. All of the features derived to estimate the expertise dimension are described in Table 3.

D. Computing objective weights using Shannon Entropy

After constructing the corresponding features to the trustworthiness and expertise dimensions, in this phase we aim to calculate the importance weight of each feature (criterion) via objective weighting. The objective weighting process is carried out separately for the two dimensions.

1) Shannon Entropy and objective weighting

Objective weighting process can be employed when it is hard for the decision makers with different interests to reach an agreement on the relative importance of the criteria (features) via a subjective weighting process. Furthermore, it can be used when suitable decision makers are not available [30]. Shannon's Entropy [14] is one of the first and most popular measures of entropy, which is a suitable method for measuring the relative contrast intensities of criteria to represent the average intrinsic information represented to the decision makers

[1] www.TripAdvisor.com

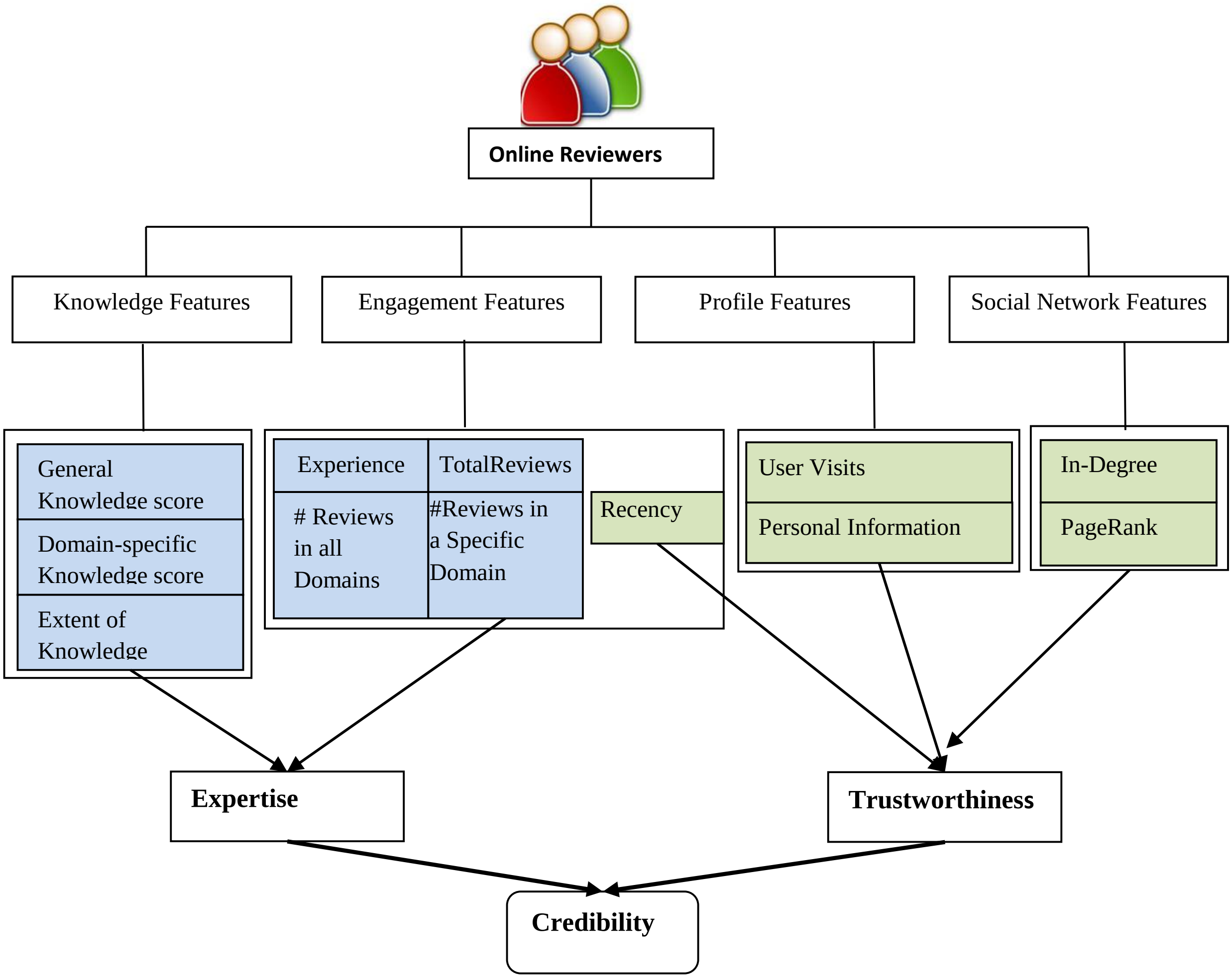

Fig. 2. Corresponding features to the source credibility dimensions

In other words, entropy measure indicates the amount of information that each criterion contains [30]. Shannon developed his measure H as follows:

$$H(p) = -\sum_i p_i \log(p_i)$$

The function H satisfies the following properties for all p_i within the estimated joint probability distribution p:

1. H is a continuous positive function.

2. If all p_i are equal, $p_i = \frac{1}{n}$, then H should be a monotonic increasing function of n.

3. For all, $n \geq 2$,
$$H(p_1, p_2, ..., p_n) = H(p_1 + p_2, p_3, ..., p_n) + (p_1 + p_2) H(\frac{p_1}{p_1 + p_2}, \frac{p_2}{p_1 + p_2}).$$

The following steps are used for determining objective weights by the Shannon's entropy [30, 32]:

Considering an $n \times m$ performance matrix (decision matrix) X as:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix}$$

Step 1: Normalize the performance matrix as:

$$p_{ij} = \frac{x_{ij}}{\sum_j x_{ij}}$$

Step 2: Calculate the entropy measure for each criterion using the following relations:

$$e_j = -k \sum_{j=1}^{n} p_{ij} \ln(p_{ij}),$$

Where $k = (\ln(n))^{-1}$ is a constant that guarantees $0 \leq e_j \leq 1$.

Step 3: Compute the degree of divergence as:

$$div_j = 1 - e_j \ .$$

Table 2: Description of features utilized to estimate trustworthiness

Feature	Description
PageRank	The page-rank of vertex i , $PR(i)$ is computed as follows. $PR(i) = c\sum_{j}\frac{PR(j)}{d_j} + 1 - c$ [22]. where j is the set of inbounding vertices of i , d_j is the out-degree of node j ,and c is the “damping factor”, a constant between 0 and 1 the graph [22]
In-Degree	In-degree centrality of a user is calculated by counting the number of paths of length one ends at a user’s nodes [31]
User visits	The number of visitors who have viewed the reviews written by the user
Number of Personal information	The number of personal information provided by a user about himself/herself
Recency	The time elapsed since the last review was written by reviewer; in other words, how long ago a reviewer wrote the last review.

Table 3: Description of features utilized to estimate expertise

Feature	Description
Experience	The length of time since reviewer membership; in other words, how long a reviewer Involves sharing and exchanging opinions.
# Reviews in all Domains	The number reviews written by reviewer in all categories during a 1 year period
# Reviews in a Specific Domain	The number of reviews written by reviewer in a specific category during a 1 year period
Total Reviews	The total number of reviews written by reviewer since the membership date
General Knowledge score	$GKS(\mathrm{i}) = \left(1 - \frac{1}{n+1}\right) \times \frac{\sum_{j\in R(u_i)} r_j}{n}$ Where n is the number of reviews written by reviewer u_i in all category during 1 year period, $R(u_i)$ is the set of reviews written by reviewer in all category during 1 year period, and r_j is the helpfulness rating of a review R_j .
Domain-specific Knowledge score	$DKS(\mathrm{i}) = \left(1 - \frac{1}{n+1}\right) \times \frac{\sum_{j\in R(u_i)} r_j}{n}$ Where n is the number of reviews written by reviewer u_i in a specific category during 1 year period, $R(u_i)$ is the set of reviews written by reviewer in a specific category during 1 year period, and r_j is the helpfulness rating of a review R_j
Extent of Knowledge	The number of categories on which reviewer has written reviews.

div_j represents the inherent contrast intensity of criterion C_j. The more div_j is the more important the criterion C_j.

Step 4: obtain the objective weights of criteria as:

$$w_j = \frac{div_j}{\sum_j div_j}$$

2) Weights of Trustworthiness Features

In this stage, we use Shannon entropy to calculate the weight of each feature described in Table 2. The calculated objective weight of each feature is shown in Table 4

3) Weights of Expertise Features

The weight of each feature relevant to expertise dimension, which is calculated using Shannon entropy, is shown in Table 5. The table illustrates the weights of features related to the expertise dimension constructed in the previous phase including experience, number of reviews in all domains (Num_rev_all), number of reviews in the specific domain (the electronic category) (Num_rev_spc), total reviews, extent of knowledge (Ext_know), general knowledge score (G_know_S) and domain-specific knowledge score (D_know_S).

4) Calculating trustworthiness and expertise scores

In this stage for each reviewer, we calculate trustworthiness and expertise scores as follows:

$$trustworthiness\_Score(i) = \sum_{j=1}^{m} x_{ij} * w^t{}_j$$

Where w^t is the objective weights vector of trustworthiness features calculated in the previous stage.

$$\text{expertise\_}score(i) = \sum_{j=1}^{m} x_{ij} * w^e{}_j$$

Where w^e is the objective weights vector of expertise features calculated in the previous stage.

E. Fuzzy Inference System for Calculating Credibility Score

As mentioned before trustworthiness and expertise are the two principal dimensions of source credibility. So far, we have proposed a systematic methodology to extract features corresponding to the trustworthiness and expertise. To accomplish this task we utilized four kinds of features including social network, profile, engagement and knowledge. In addition, as depicted in the previous section, we utilized Shannon entropy measure to find the objective weights of features. Finally, for each reviewer, we computed trustworthiness and expertise scores.

In reality, we generally do not use crisp numeric number values to evaluate credibility or other aspects of a person but we use linguistic terms like *small* and *large*. To build a realistic credibility rank for reviewers we follow cognitive approach. We covert the numeric values which were calculated for expertise and trustworthiness dimensions to linguistic terms and use them to reason about the credibility of reviewers.

We use a fuzzy inference system (FIS) [33] to calculate a comprehensive credibility rank for each reviewer. The fuzzy inference systems can be considered as methods that use the concepts and operations from the fuzzy set theory and by fuzzy reasoning methods [34]. There are several studies related to the design techniques involving fuzzy inference systems. Among these techniques, Mamdani fuzzy inference system (Mamdani & Assilian, 1975 is one of the most popular algorithms which is used in this paper. This method uses the concepts of fuzzy sets and fuzzy logic [35] to translate an entirely unstructured set of linguistic heuristics into an algorithm.

A fuzzy inference system as portrayed in Fig. 3 consists of four main parts (1) Fuzzification, (2) fuzzy rule base, (3) fuzzy inference system, and (4) defuzzification. We will describe each part of the constructed fuzzy inference system in detail.

Table 4: The objective weights of features related to the trustworthiness

Feature	In-Degree	PageRank	User Visits	Personal Information	Recency
Weight	0.2684	0.2319	0.3202	0.1566	0.0229

Table 5: The objective weights of features related to expertise

Feature	Experience	Num_rev_all	Num_rev_spc	Total reviews	Ext_know	G_know_S	D_know_S
Weight	0.0547	0.2593	0.3686	0.2607	0.0386	0.0101	0.0079

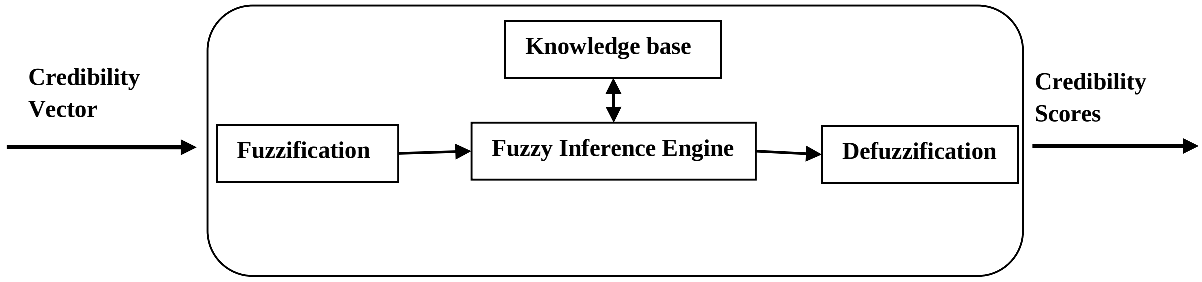

Fig. 3. Fuzzy inference system designed for calculating credibility

1) Fuzzification

The fuzzification refers to the process of converting crisp values into grades of membership for linguistic terms of fuzzy sets. The membership function is used to associate a grade to each linguistic term. In other words, input vector (crisp values) can be translated into linguistic terms, such as small and large with the help of membership function (MF). Membership functions have different types of linear and nonlinear shape. The trapezoidal or triangular fuzzy sets are widely used MFs due to their computational efficiency [36].

In our system, corresponding to each input variable, we define a linguistic variable. Each linguistic variable consists of a set of linguistic terms, for examples low, medium and high. Each linguistic term is represented by a MF, which is denoted by μ . The Fuzzifier uses these MFs to convert crisp input variables into linguistic terms.

As illustrated in Fig. 3, in our system the input variables are credibility dimensions including trustworthiness and expertise values of reviewers. Therefore, in our system, we have two input variables and the output variable is credibility. The input variables are arranged in three linguistic terms – Low, Medium and High – represented by three trapezoidal MFs applied in each variable as illustrated in Fig. 4.

In addition, the output variable (credibility) consists of five linguistic terms – Very Low, Low, Medium, High and Very High - represented by five trapezoidal MFs depicted in Fig. 5.

2) Knowledge Base

Knowledge base consists of a database and rule base. MFs are defined by database and fuzzy if-then rules form the rule base. A fuzzy if-then rule is generally made up of a premise (antecedent) and a consequent (conclusion) part for example “if x is high (premise) then y is low (consequent)” where the terms high and low can be represented by MFs [33]. A fuzzy rule indicates the conditions in which a set of fuzzy inputs can be translated into a fuzzy output variable.

Since we have 2 input variables and each of which can have 3 different values, we will have $3^2 = 9$ different combinations. Each combination can potentially correspond to a particular level of credibility. Definition of credibility can be different according to the specific context. Therefore, here we define some fuzzy rules to compute credibility of reviewers. It is important to note that one of the main advantages of our system is that it allows system users to customize their credibility definition by defining any number of fuzzy rules they need. In our proposed system, we have defined 9 rules for all possible combinations and demonstrated them in Table 6.

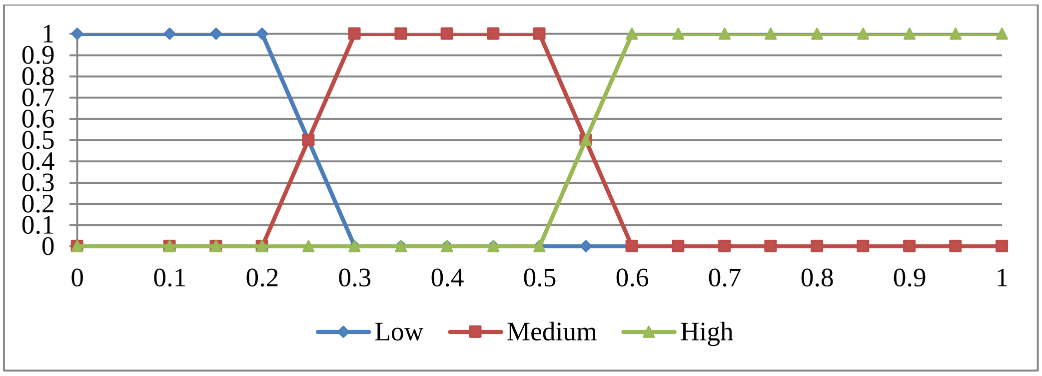

Fig. 4.Membership functions of the input variables

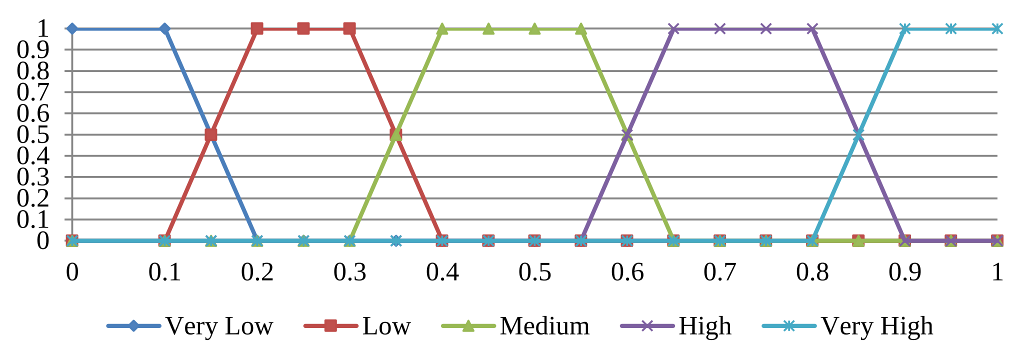

Fig. 5. Membership functions of the output variable

Table 6: The set of fuzzy rules defined in our system (VL = Very Low, L = Low, M = Medium, H = High, VH = Very High)

Rule no.	Input variables		Output variable
	Trustworthiness	Expertise	Credibility
1	H	H	VH
2	H	M	H
3	H	L	M
4	M	H	H
5	M	M	M
6	M	L	L
7	L	H	M
8	L	M	L
9	L	L	VL

3) *Fuzzy Inference Engine*

In this stage, the fuzzy inference engine uses the defined fuzzy if-then rules to assign a map from fuzzy inputs to fuzzy outputs based on fuzzy composition rules [37]. This step is the key part of a fuzzy expert system that aggregates the facts derived from the fuzzification process with the rule base and caries out the modeling process.

As explained earlier, several fuzzy inference systems have been applied in various applications. Mamdani fuzzy inference system [38] is one of the most popular algorithms. The general "if-then" rule form of the Mamdani algorithm is given in the following [39]:

$$\mathrm{R}_i\text{: IF } u_1 = \mathrm{A}_{i1} \text{ AND } u_2 = \mathrm{A}_{i2} \text{ AND } \cdots\ u_p = \mathrm{A}_{ip}$$
$$\text{THEN } y = \mathrm{B}_i, \mathrm{i} = 1, \ldots, \mathrm{M}$$

Where $u_1, \ldots, u_p$ are the p inputs of the fuzzy system gathered in the input vector $\underline{u}$, y is the output, M is the number of fuzzy rules, A_{ij} denotes the fuzzy set (linguistic term) used for input $u_j\,(j = 1, \ldots, p)$ in rule i, B_i is the fuzzy set used for output in rule i.

In the inference engine the following steps must be carried out [39]:

- Aggregation: in this step, for each rule i the degree of fulfillment is computed by applying the min operator as follows:

$$\mu_i(u) = \min[\mu_{i1}(u_1), \mu_{i2}(u_2), \cdots, \mu_{ip}(u_p)]$$

- Activation: in this step, the degrees of rule fulfillment which are calculated in the aggregation step, are utilized to calculate the output activations of the rules by this relation

$$\mu_i^{act}(\underline{u}, \mathrm{y}) = \min[\mu_i(\underline{u}), \mu_i(\mathrm{y})],$$

Where $\mu_i(y)$ the output of MF is associated with fuzzy set B_i, and $\mu_i(\underline{u})$ is the degree of fulfillment for rule *i*.

- Accumulation: in this step, the output activations of all rules are aggregated using the max operator as follows:

$$\mu^{acc}(\underline{u}, y) = \max[\mu_i^{act}(\underline{u}, \mathrm{y})]$$

4) *Defuzzification*

Defuzzification process is used to convert the fuzzy output into a crisp value. There are several defuzzifier methods in the literature. Centroid of area (COA) [40] is one of the most prevalent methods for defuzzification process; it is given by the following algebraic expression:

$$y^*_{COA} = \frac{\int_{y_{\min}}^{y_{\max}} \mu^{acc}(\underline{u}, y)\, y\, dy}{\int_{y_{\min}}^{y_{\max}} \mu^{acc}(\underline{u}, y)\, dy}$$

Where Y^*_{COA} is the crisp value for output variable y [39].

F. *Application of the proposed framework*

So far, we have accomplished all phases of the proposed framework for ranking reviewer in terms of credibility. Firstly, we identified the main factors influencing reviewers' credibility; secondly we crawled the required data and constructed the features related to reviewer credibility; therefore, each reviewer is represented by a vector features; thirdly we used Shannon entropy to obtain importance weights of features; for each reviewer, using the features vector and obtained importance weights, the trustworthiness and experience scores were calculated. Finally, we designed a system for calculating reviewers' credibility using fuzzy inference system.

The results of applying the proposed framework for ranking reviewers in terms of credibility are shown in

Table **7**. The proposed framework can help consumers in finding credible reviewers and reviews and there by facilitating, purchase decisions. Besides, companies can employ the framework to gain insights about customers' opinions and sentiments regarding their products and services in an efficient and effective manner. One of the main advantages of the presented framework is that it exploits four types of features pertinent to the source credibility dimensions to calculate reviewers' credibility scores. This is in contrast with the existing studies [11, 13] which have considered only number of reviews posted by a reviewer and helpful votes received by each reviews to compute credibility of reviewers. Another main attribute of the framework is taking cognitive approach in calculating credibility scores. To the better of our knowledge this is the first study that uses fuzzy inference to quantify reviewer credibility. In reality, we generally do not use crisp numeric number values to evaluate credibility or other aspects of a person but we use linguistic terms like *small* and *large*. To build a realistic credibility rank for reviewers we follow cognitive approach and exploit fuzzy inference system.

V. Analysis and Discussion

According to what mentioned earlier, one problem in mining online reviews is that online reviews vary greatly in terms of credibility and quality. Therefore, considering all online reviews (credible and less credible) cannot be a reasonable approach since the mining results may not be useful. The proposed approach can be utilized by both online communities and firms to find credible reviewers and then selecting the reviews written by those reviewers. The rationale behind doing so is that credibility assessment of source (reviewer) and message (review) are fundamentally and positively interlinked [11].

We believe that our proposed approach for ranking reviewers is very effective and practical since it rank reviewers using fuzzy inference system based on source credibility dimensions that are well studied in literature. To illustrate an application of the presented method, we applied it for ranking reviewers of Epinions.com. The main strong point of our approach is exploiting useful features corresponding to the credibility dimensions. The existing mechanisms for ranking reviewers consider only a limited number of features. For instance, the ranking method used by Epinions is the popular author ranking method, which is calculated based on the total hits to user's reviews. Therefore, on Epinions, popular author ranking is performed using the total hits measure. Based on what features we have utilized in the proposed approach, it is clear that our approach is not limited to one measure and operates based on the source credibility dimensions studied in literature. In addition, studies in the credibility context only try to find the factors affecting credibility of users. These studies did not present a practical mechanism for quantifying users' credibility. Furthermore, another contribution of our paper is taking a cognitive approach in quantifying credibility. That is we quantify the final credibility score by employing a fuzzy inference system. To the best of our knowledge, this is the first study that follows such approach.

To evaluate the results of the proposed method, we checked the data of the top 10 ranked reviewers resulted from applying the method. We find out that the top ranked reviewers outperform other reviewers in terms of the utilized features (e.g. features extracted relevant to credibility dimensions). In sum, we can conclude that our proposed method for ranking reviewers is superior than other ranking mechanisms for the following reasons: (1) it utilizes some useful and informative features derived from four categories of data corresponding to source credibility dimensions to quantify reviewers credibility; this study is in contrast to the similar study [11] that only utilized one or two features for that purpose. (2) As in reality, we generally do not use crisp numeric number values to evaluate credibility or other aspects of a person but we use linguistic terms like small and large. To build a realistic credibility rank for reviewers we follow cognitive approach, therefore we use a fuzzy inference system (FIS) (Jang, Sun, & Mizutani, 1997) to calculate a comprehensive credibility rank for each reviewer (3) checking the results of ranking shows that the top ranked reviewers outperform other reviewers in terms of the employed features.

As mentioned before, our proposed approach is based on exploiting four categories of features in order to quantify reviewers' trustworthiness and expertise. These categories include trust network, profile, engagement and knowledge features. The idea of our approach in some part is somewhat similar to that of search engine like Google. Google employs a number of techniques to improve search quality including PageRank, anchor text, and proximity information. In other words, Google utilize web graph and content of each web page to compute an overall ranking score for each webpage.

Table 7: Top 10 credible reviewers identified using the proposed framework

Rank									
1	2	3	4	5	6	7	8	9	10
Rev#75	Rev#29	Rev#57	Rev#95	Rev#103	Rev#166	Rev#162	Rev#81	Rev#157	Rev#177

Our approach calculates each reviewer's popularity in his/her web of trust using PageRank. In addition, it considers reviewer's level of contribution and knowledge to quantify his/her credibility dimensions. Therefore, based on source credibility concept, our approach employs a number of features to rank reviewers effectively.

VI. CONCLUSION

In an online product review website, due to the lack of a comprehensive mechanism to validate online reviews some low quality and uninformative online reviews may be produced. In this paper, to tackle review quality problem, we addressed reviewer credibility since credibility assessment of reviewer and review are fundamentally and positively interlinked. A novel framework to rank reviewers in terms of credibility was proposed. The framework consists of five major phases: (1) identifying reviewer credibility dimensions (2) crawling the required data (3) deriving the relevant features to the identified dimensions (4) calculating importance weights of features (5) designing fuzzy inference system for calculating credibility scores To illustrate an application of the proposed method, we conduct an experimental study using real data gathered from Epinions.

The main contributions of this paper are utilizing four types of features including social network, profile, engagement and knowledge feature in measuring reviewers' credibility dimensions; using entropy measure to calculate features weights; designing a fuzzy inference system to estimate credibility scores. To the better of our knowledge this is the first study that uses fuzzy inference to quantify reviewer credibility. In reality, we generally do not use crisp numeric number values to evaluate credibility or other aspects of a person but we use linguistic terms. Thus, to build a realistic credibility rank for reviewers we pursued a cognitive approach and exploited fuzzy inference system.

The proposed framework can support marketing departments in identifying the most credible reviewers and thereby focusing on their informative and realistic comments and feedbacks about their products and services in an efficient and effective manner. By analyzing the most credible reviewers' feedbacks, a firm can understand the actual strengths and weaknesses of their offered products so it can take effective and efficient decisions to improve its products quality.

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