W2Q: A Dual Weighted QoI Scoring Mechanism in Social Sensing using Community Confidence

Shameek Bhattacharjee, Nirnay Ghosh, Vijay K. Shah, and Sajal K. Das
Department of Computer Science,
Missouri University of Science and Technology, Rolla, MO
Email: {shameek, ghoshn, vksr38, sdas}@mst.edu.

***Abstract*—A significant vulnerability in social sensing based services is false notifications from sensing agents, thereby resulting in inaccurate published information that induces loss of revenue and business goodwill. Existing popular schemes utilize rating feedbacks (over the published information) to quantify the perceived usefulness (quality) of the information. However, these schemes do not reward the confidence of the feedback community and lacks provision to regulate the impact of uncertain feedbacks (ratings), and hence can be easily manipulated. In this paper, we propose a model, called $W2Q$, to mathematically evaluate the *Quality of Information (QoI)* as a function of the proportion of positive ratings, total number of ratings, and amortized proportion of uncertain ratings. The proposed model exploits Bayesian inference, and a dual weighted regression model to compute the QoI of any published information. We evaluate the proposed model through an experimental study assuming a crowd sourced-urban application as a proof of concept. Experimental results show that compared with the state-of-the-art Jøsang's belief model, the resultant QoI score is less susceptible to rogue ratings and captures subtle differences between true and false information.**

***Index Terms*—Trust, Crowd Sourcing, Pervasive Computing, Information Quality**

I. Introduction

Recent years have witnessed a splurge in commercial services leveraging "social sensing" paradigm to publish summarized statistics (*information*). The sensing agents in this paradigm could either be automatic sensors, called *auto sensing (AS)*, or voluntarily participating human users, called *crowd sensing (CS)*, who use their smart mobile devices to send *notifications*. Each sensing agent monitors its local environment and sends alert message to a remote server whenever it perceives an event of interest. Such notifications (possibly of different modalities) sent by either AS or CS are aggregated by the service provider to generate a summarized information. This information is then broadcasted to other users (consumers) through different media to support better decision making and thus, improve the quality of service.

One prominent example of AS-based social sensing is the *Total Traffic & Weather Network (TTWN)*[1] which has developed massive sensing infrastructures in major cities across the USA to capture traffic, transit, and weather data. Commuters, drivers, and other users access such information in real-time from the Twitter accounts maintained by TTWN. Followers of those accounts are eligible to *like*, *share*, *reply* or *retweet* against the generated messages. Similarly, some CS-based applications worth mentioning are *Waze*[2] and *Nericell*, which receive notifications on road conditions to improve navigation experiences through dynamic route planning. Other CS-based application like *FourSquare*, *Yelp*, and *YikYak* recommend ideal point of interests in geographical proximity.

A major drawback with both the social sensing mechanisms is the generation of false notifications. In case of AS, incorrect data may be generated if one or more sensing devices become faulty or are compromised by adversaries. For example, a false traffic jam or weather hazard may be notified, making the service provider believe that such event has really occurred. If the provider persists with incorrect (or false) information for longer periods of time, the consequences may be serious.

In contrast, CS allows human users (contributors) to voluntarily participate (typically in exchange of incentives) and generate notifications on perceived incident. However, the "open" nature of the CS paradigm exposes the applications to erroneous and dishonest contributions [4]. Several CS applications use credit based incentive schemes [11] [10] to motivate users to be active participants and sustain a steady flow of contributions. In most incentive schemes, the degree of participation (i.e., how much the users contribute), rather than the correctness of the submitted data, is used as the criterion for rewards. Consequently, dishonest users misuse such reward mechanisms to generate false notifications and gain unfair incentives [13]. In many instances a group of sensing agents may collude [15] to make the false information believable to the provider. If the false published information is not detected quickly, consequent impacts could be drastic [14].

In [1], the authors have studied real data sets of Waze application which confirms the presence of bogus notifications and their negative impact on the incentive mechanism. Thus, irrespective of reasons for generating false notifications in both AS and CS, loss of revenue and trustworthiness are inflicted on the service provider. Therefore, there is a need to estimate the *quality of information (QoI)* generated by the sensing agents.

Some existing literature [4], [13] dealing with real systems use the rating feedback paradigm to gain an estimated perception of truthfulness or QoI of a published information. The underlying trust models [6], [7] measure QoI as the fraction of positive ratings. However, these approaches do not account

[1]http://www.ttwnetwork.com/

[2]www.waze.com

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for the confidence of the community (total number of ratings), null invariance (high uncertainty or inconclusive association should not be allowed to influence correlations), and fraction of uncertain ratings that may negatively influence the QoI.

In this paper, we propose a novel QoI scoring model, termed as $W2Q$, which unifies both the proportion of positive ratings and the confidence of the community, while accommodating the provision to regulate uncertainty using amortized proportion of uncertain ratings. Consideration of both of these attributes nullifies the effect of possible rogue ratings on the existing QoI measures and sparse ratings. We use Bayesian inference to calculate the probability masses for different rating categories viz., *Useful*, *Not Useful*, *Not Sure*. Then we calculate an expected truthfulness of the information based on regression with dual weights that capture the number of ratings and the amortized proportion of uncertainty mass depending on the risk attitude of the provider. The expected truthfulness is mapped into a QoI using a *link* function. Experimental results establish that compared to Jøsang's belief model, the resultant QoI score is less susceptible to rogue ratings and captures subtle differences between true and false information.

The rest of the paper is organized as follows. Section II presents related works and their limitations to draw motivations. Section III describes the system and threat models. Section IV presents the proposed QoI scoring model. Extensive simulation results are presented in Section V while conclusions are drawn in Section VI.

II. Related Work and Motivation

Existing works on quality of information (QoI) in social sensing paradigms primarily deals with its improvement. The following literature review is primarily based on CS paradigm.

The QoI improvement has been mainly attempted through design of incentive mechanisms and selection of sensing agents. The primary objective of incentive mechanisms is to motivate the users to contribute with correct sensing data. It has two variants: *online* and *offline*. For online type, the system is trained by the first batch of participants, and tested on the subsequent batches [18], [19]. Conversely, for offline type, the incentivization system receives apriori information about the participants, and then uses *reverse auction* mechanism for bidding and winner selection [5], [3]. Selection of human sensing agents is based on their location proximity to the event [3].

The fundamental differences between our proposed QoI scoring model, $W2Q$ and existing works are as follows. First, many existing works such as [18], [19] focus on the selection of trusted sensing agents, and incentives mechanisms that motivate participation to improve the QoI. However, once agents had generated the notifications, assessing the extent of truthfulness of the summarized information is largely missing. In contrast, $W2Q$ focuses on quantifying the QoI, given the possibilities of false notifications from sensing agents. Second and most importantly, our work proposes a mathematical quantification of QoI that ameliorates the following limitations existing in the state-of-the-art (Jøsang's belief and its variants) approaches of evaluating QoI from the ratings:

Confidence of Rating Community: Jøsang's belief model, and its variants such as Beta reputation [8] uses several variants of the expected ratio between number of positive ratings to the total number of ratings as the QoI metric. However, such models do not capture a fundamental aspect which we term as *confidence of the community*. This feature, if not incorporated makes QoI vulnerable to manipulation when dishonest raters provide positive ratings to useless and bogus information (known as *ballot stuffing*) and negative ratings to true or authentic information (known as *bad mouthing*).

This is illustrated in Table I. Each usecase in the table is represented as a four tuple $U : \langle N, r, s, t \rangle$, where N is the total number of received ratings, while r, s, and t respectively denote the number of positive, negative, and uncertain ratings. The details of Josang's QoI model is provided in Section V-A.

The first row in Table I shows that usecase $U1$ has 4 good ratings out of 8 total ratings, whereas $U2$ has 40 such ratings out of 80. Jøsang's belief model measures almost same QoI for both usecases. From an adversary's viewpoint, it is easy to manipulate 4 good ratings by compromising 4 raters and maintain the same fraction of positive ratings as $U2$. However, it is harder to maintain the same when the crowd is large (as in $U2$), where the adversary has to compromise 40 raters. Hence, given the same fraction of positive ratings, the information with a higher number of ratings (i.e., confidence of the community) should be much more trustworthy.

Controlling the Effect of Uncertainty: As aforestated, the QoI of a false information can also be increased due to many undecided ratings which may be deliberately faked or a result of legitimate uncertainty in the rating feedback mechanism. Jøsang's belief model or closely related Dempster Shafer based reputation cannot differentiate between scenarios with high and low uncertainties. An illustrative example is shown in second row of Table I. Usecase $U3$ has 105 ratings out of which 100 are uncertain; however it achieves almost same QoI as $U4$ which in contrast has only 20 uncertain ratings. Hence, this QoI measure suffers from null-invariance. For certain conservative services, it may be risky to give such a high QoI to $U3$, as opposed to $U4$. Thus, the QoI measure needs a provision for controlling the impact of higher uncertainty on the QoI.

III. System and Threat Models

A. System Model and Design

As depicted in Figure 1, our system model captures a particular urban area which may consist of both auto-configured sensors and smartphone users, to collect various sensing data viz., air and sound pollution, traffic, and so on. Two important components of this system are:

Notification: A notification is an alert generated by a sensing agent (sensor or human) in response to its perception of an incident of relevance. However, due to malfunctioning or adversarial attack on one or more sensing devices, or presence of dishonest users, there may be false notifications.

TABLE I
LIMITATIONS OF JØSANG'S BELIEF MODEL

Issues	Use Cases	Jøsang QoI	Comment
Confidence of Rating Community	U1: $\langle 8,4,2,2\rangle$	0.59	No significant difference in expected truthfulness. Does not
	U2: $\langle 80,40,20,20\rangle$	0.61	award confidence of the community
Not Null Invariant	U3: $\langle 105,5,0,100\rangle$	0.51	Expected truthfulness is fairly high in $U3$
	U4: $\langle 25,5,0,20\rangle$	0.53	even though majority ratings are "undecided"

Information: An information I_k, $k \in \{1, \cdots, K\}$ is a message which is published in some form (e.g., on live map) after the service provider receives a pre-defined number of "similar" notifications. K is the total number of such information published over a given time span.

In the system model, there exists two types of actors:

Sensing agent: A sensing agent is either a sensor or human user who has a proclivity to generate notifications. Furthermore, to remove biases from the ratings, a sensing agent is not allowed to rate a published information for which it has generated a notification.

Rater: A rater is a human user who provides a rating based on his utility of a published information through one of these categories: *Useful* (α), *Not Useful* (β), and *Not Sure* (γ).

For a published information, only one rating can be submitted by each rater. We consider the act of providing rating as a choice, and there is no mechanism to incentivize users. Hence, for majority of the neutral users, there is no selfish incentive to provide false ratings. However, raters could be motivated in a malicious manner as discussed in the threat model in the next subsection. In general, we consider the number of ratings to be higher than the number of notifications which is also evident from the *Epinions* dataset [12].

The primary design principle of the proposed $W2Q$ scoring model should be to collect higher number of ratings to get a notion about the truthfulness of the information in absence of the ground truth. This may be achieved through auto-activation of a pop-up rating query during an active rater's transit through the vicinity of the published information.

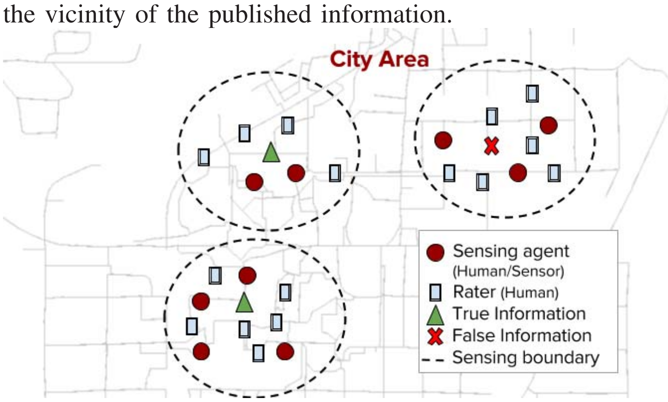


Fig. 1. System Model

B. Threat Model and Assumptions

As mentioned earlier, sensing agents can be either auto-configured sensors (auto sensing) or human users (crowd sensing). The sensors can generate false notifications either due to hardware/software fault or adversarial manipulations. If one or more sensors are compromised, they can be made to act dishonestly. On the contrary, human users may also behave dishonestly in the following ways: (i) intermittently act as malicious agents to gain undue incentives, and (ii) persistently act as dishonest agents, either through collusion or by generating several fake logical interfaces (sybils) to tarnish the goodwill of the application.

For raters, we assume that they can also collude among themselves to provide false ratings as follow:

Bad mouthing: The rater provides negative ratings to an authentic published information.

Ballot stuffing: This attack arises when the rater provides positive ratings to an incorrect (false) published information.

IV. $W2Q$: PROPOSED QOI SCORING MODEL

The proposed QoI scoring model consists of three major modules. The first module derives the posterior probability masses for each rating category. The second module calculates the expected truthfulness of a published information by estimating appropriate *weights (coefficients)* of belief and uncertainty masses using logistic and stretched exponential functions, respectively. Finally, the third module calculates of a real valued QoI for each published information using a logit link function. A flow diagram of the different modules along with the inputs and outputs are shown in Figure 2.

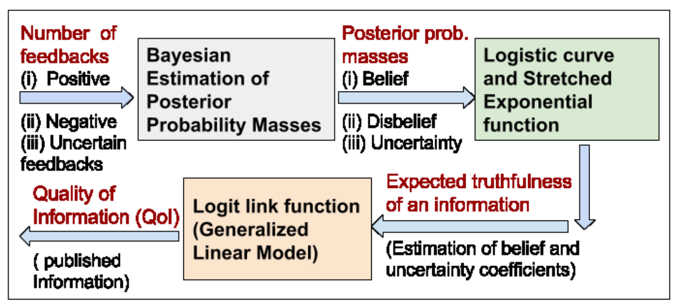


Fig. 2. $W2Q$: Flow Diagram

A. Derivation of Posteriori Probability Masses

The first step is to derive the posteriori probability masses associated with the published information being 'Useful', 'Not Useful' and 'Not Sure'. The probability masses are calculated for each information I_k. For better readability, I_k is removed from all the notations. The posteriori probability mass of each rating category should be based on the available evidence (i.e., support for each rating type). A classical Bayesian approach has been considered for estimation of probability masses.

Let $\bar{\theta} = \{\theta_\alpha, \theta_\beta, \theta_\gamma\}$ be the three tuple probability parameter to be estimated. Here, $\theta_\alpha, \theta_\beta, \theta_\gamma$ are the unknown probabilities of observing a Useful, Not Useful, or Not Sure ratings, respectively. We denote $H(\bar{\theta})$ as the hypothesis, such that it has three possibilities corresponding to α, β, and γ. Formally the corresponding probabilities are given by:

$$\begin{aligned} P(H(\bar{\theta}) = \alpha|\bar{\theta}) = \theta_\alpha \\ P(H(\bar{\theta}) = \beta|\bar{\theta}) = \theta_\beta \\ P(H(\bar{\theta}) = \gamma|\bar{\theta}) = \theta_\gamma \end{aligned} \tag{1}$$

Let F_α, F_β, and F_γ be the random variables denoting the number of ratings η_α, η_β, and η_γ, received for each possible rating category, respectively, such that $N = \eta_\alpha + \eta_\beta + \eta_\gamma$. The *evidence* vector, denoted as $F(N) = \{F_\alpha, F_\beta, F_\gamma\}$, should be modeled as a multinomial distribution given by:

$$\begin{aligned} P(F_\alpha = n_\alpha, F_\beta = n_\beta, F_\gamma = n_\gamma|\bar{\theta}) = \\ P(F(N)|\bar{\theta}) = \frac{N!}{n_\alpha! n_\beta! n_\gamma!} \theta_\alpha^{n_\alpha} \theta_\beta^{n_\beta} \theta_\gamma^{n_\gamma} \end{aligned} \tag{2}$$

The posteriori hypothesis based on the evidence vector and assumed prior is given as:

$$\begin{aligned} P(H(\bar{\theta}) = \alpha|F(N)) = \frac{P(H(\bar{\theta}) = \alpha, F(N))}{P(F(N))} \\ P(H(\bar{\theta}) = \beta|F(N)) = \frac{P(H(\bar{\theta}) = \beta, F(N))}{P(F(N))} \\ P(H(\bar{\theta})) = \gamma|F(N)) = \frac{P(H(\bar{\theta}) = \gamma, F(N))}{P(F(N))} \end{aligned} \tag{3}$$

First, we calculate

$$P(H(\bar{\theta}) = \alpha|F(N)) = \frac{P(H(\bar{\theta}) = \alpha, F(N))}{P(F(N))} \tag{4}$$

The denominator $P(F(N))$ of Eqn. (4) is the marginal probability, conditioned on all possibilities of $\bar{\theta}$. The numerator is a combination of likelihood and the prior $f(\theta)$. Since $\bar{\theta}$ is continuous, the denominator of Eqn. 4 can be written as:

$$P(F(N)) = \int_{F(N)(\bar{\theta})} P(F(N)|\bar{\theta}) f(\bar{\theta}) d(\bar{\theta}) \tag{5}$$

Similarly, the numerator of Eqn. (4), can be written as:

$$P(H(\bar{\theta}) = \alpha, F(N)) = \int_{F(N)(\bar{\theta})} P(H(\bar{\theta}) = \alpha, F(N)|\bar{\theta}) f(\bar{\theta}) d(\bar{\theta}) \tag{6}$$

Eqns. (5) and (6) can be solved and plugged into Eqn.(4). The details of this procedure is provided in [2]. Following that, it can be shown:

$$P(H(\bar{\theta}) = \alpha|F(N)) = \frac{\eta_\alpha + 1}{N + 3} = b \tag{7}$$

For other hypothesis in Eqn.(3), it can be similarly shown that

$$P(H(\bar{\theta}) = \beta|F(N)) = \frac{\eta_\beta + 1}{N + 3} = d \tag{8}$$

$$P(H(\bar{\theta}) = \gamma|F(N)) = \frac{\eta_\gamma + 1}{N + 3} = u \tag{9}$$

Eqns. (7), (8), and (9) are the posteriori probability masses for *Useful*, *Not Useful*, and *Not Sure* as perceived by the raters, respectively. The masses are referred as belief (b), disbelief (d), and uncertainty (u) masses. For verification of correctness, it can be shown that $b + d + u = 1$. Additionally, when $\eta_\alpha = \eta_\beta = \eta_\gamma = 0$, all the possibilities are equiprobable under no information (non-informative prior).

B. *Expected Truthfulness of Published Information*

For computing the expected truthfulness, we apply the logistic function and the stretched exponential function to estimate the weights of belief and uncertainty masses, respectively. The problem is modeled similar to a weighted regression approach where probability masses are independent (predictor) variables and the expected truthfulness is a dependent (response) variable. Thus, if w_b and w_u are the coefficients (or weights) of belief and uncertainty masses respectively, the expected truthfulness for any published information I_k will be given as:

$$\tau_k = (w_b).b + (w_u).u \tag{10}$$

1) Estimation of the Belief Coefficient: Apart from the probability masses, the expected truthfulness should also consider the confidence of the community, i.e., how many ratings have been received for the concerned piece of information. Intuitively, lesser N (total number of ratings) should have low w_b, which in turn, contributes to a lesser expected truthfulness. However, w_b should gradually increase as more ratings are available. Thus, to model this nature of w_b we use the logistic function in the following way:

$$w_b = \frac{1}{(1 + A_b e^{-B_b N})} \tag{11}$$

where A_b is the initial value of the weight, and B_b is the rate of growth. More conservative (or high risk applications) systems will have less A_b and B_b. This provision gives control to the system administrator to thwart the extent of ballot stuffing and bad mouthing. This is because QoI based on only belief masses usually get influenced in favor of the adversaries if there are limited number raters in the system. However, if a large crowd of independent raters is present, it may not be possible to sabotage the entire proportion of positive ratings in the adversary's favor. Hence, the administrator should choose B_b such that N is large enough to prevent sabotaging.

2) Estimation of the Uncertainty Coefficient: In Eqn. (10), w_u controls the contribution of uncertainty to the effective belief. In general, if an incident has just occurred, and sufficient notifications have not been received to establish a consensus, uncertainty will be increasing. As this increase is also similar to growth curve, we estimate the coefficient in terms of logistic function. However, as more ratings are available over time, this uncertainty in the perceived truthfulness of the gained information gets reduced. Thus, once the number of ratings reaches a threshold value, say $N = N_{thres}$, the coefficient should start to gradually decrease.

A stretched exponential function has been used to model the decay aspect of the uncertainty and its parameter $0 < \varphi < 1$ controls the diminishing rate. Hence, after $N = N_{thres}$, this function is used to amortize the w_u over N. The larger the value of φ, the quicker is the decrease. Eqn.(12) gives the variation of w_u with respect to the number of received ratings:

$$w_u = \begin{cases} \frac{1}{(1+A_u e^{-B_u N})}, & \text{if } N < N_{thres} \\ e^{-(N-N_{thres})^\varphi}, & \text{if } N \geq N_{thres} \end{cases} \tag{12}$$

where A_u and B_u are respectively the corresponding asymptote and growth parameters, as discussed in Eq. (11).

C. QoI of Published Information

In Eqn. 10, τ_k is the expectation that the published information I_k has actually happened. Now, the system needs to perform a regression to determine the odds of I_k being true or false which we model as the QoI. We have used the *generalized linear model (GLM)* for this purpose. When the response/predictor variables is categorical (true/false, yes/no, etc.) with non-normal error distribution, we need a *link* function to provide the relationship between the predictor variable (linear) and the mean of the distribution (explanatory) defining the QoI. Thus, if Q_k is the response and τ_k is the mean, the link between them is established by the following logit function:

$$Q_k = \ln\left(\frac{\tau_k}{1-\tau_k}\right) \tag{13}$$

Here, Q_k is the QoI of the published information I_k which has value in the interval $[-\infty, +\infty]$. The logit function gives monotonically decreasing QoIs to all $\tau_k < 0.5$, and monotonically increasing ones to the rest.

V. Performance Study

In this section, we present analytical and simulation results of $W2Q$ and compare it with Jøsang's belief model.

TABLE II
USE CASES: COMPARATIVE QOI

Usecases	Jøsang's Model	Model $W2Q$
$\langle 8,4,2,2\rangle$	0.59	0.05
$\langle 80,40,20,20\rangle$	0.62	0.54
$\langle 105,5,0,100\rangle$	0.54	0.27
$\langle 25,5,0,20\rangle$	0.58	0.16
$\langle 25,18,2,5\rangle$	0.79	0.25
$\langle 100,72,8,20\rangle$	0.81	0.75

A. Analytical Results

Let us compare our QoI scoring model with Jøsang's expected truthfulness (E^J) which is equivalent to τ_k in our approach (because the scale of both metrics have to be between 0 and 1 for fair comparison). Jøsang's belief model is given by the following: $b = r+1$; $d = s+1$; $u = t+1$; $E^J = b + a.u$, where $a = 0.5$. The amortization factor in Jøsang's belief model known as relative atomicity is fixed as the reciprocal of the cardinality of inference state space (i.e. true or false information) [7].

Table II presents a comparative analysis of the QoI generated by two approaches. Two important observations are: (i) $W2Q$ rewards those scenarios which has the higher community confidence, and (ii) unlike Jøsang's model, $W2Q$ does not suffer from the risk of null-invariance.

B. Simulation Results

This section depicts the details of simulation settings, empirical comparison with Jøsang's belief model, and efficiency of $W2Q$ in terms of distinguishing true and false information.

1) Simulation Settings: For experiment, an urban sensing application (viz., air pollution, traffic, etc.) which receives crowd-sourced notifications, has been considered. We simulate a city with an area of 100×100 sq. units as the sensing region. Let there be M sensing agents and N raters in the region, where $N \geq 2M$ as extrapolated from Epinions dataset [12]. The region is equally divided into four sub-regions, each of which is initialized with $\frac{M}{4}$ sensing agents and $\frac{N}{4}$ raters. Here, we consider $M = 800$ and $N = 1600$.

Out of M sensing agents, 85% are considered to act as honest agents whereas the rest as dishonest. An honest agent sends notification for perceived true information with atleast 90% probability whereas a dishonest agent behaves the same for a fake incident (that has not actually happened). It is noteworthy that a dishonest agent may also send notification for true information with probability between 5% and 40%.

Out of N raters, we consider at least 75% will rate the published information correctly if any such rater lies in the sensing boundary (< 10 sq unit) of the published information. Whereas, the rest of the raters are dishonest by nature. They give positive ratings to false information and negative ratings to true information. These considerations are made to replicate the aforementioned threat model (section III-B).

The total sensing duration is uniformly divided into T discrete number of time spans, where each span represents a fixed time interval unit (such as 30 minutes). In each time span, there is a pre-specified likelihood of occurrence of true and/or false incident. Within a certain radius (10 sq. unit) of the incident, each sensing agent is likely to send notifications for it. Similarly, each rater is liable to rate the published information for the same.

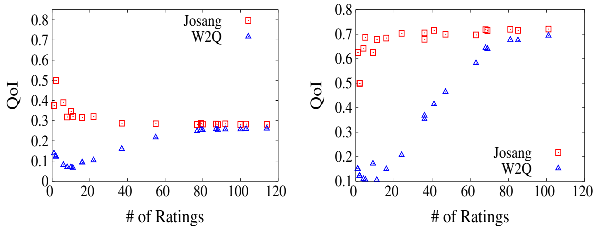
For human mobility model, we consider a simple random waypoint model where each human agent including rater would have non-zero probability to move in any direction. However, auto-configured sensors are fixed.

Unless otherwise stated, we consider following parameter values for the simulation: $A_b = A_u = 20$, $B_b = B_u = 0.08$, $\varphi = 0.2$ and $N_{thres} = 40$.

2) Comparative Analysis with Jøsang's Belief Model: Fig. 3(a) shows the comparison between QoI achieved by $W2Q$ and Jøsang's belief model for false published information. We observe that $W2Q$ does not provide undue high QoI to the published information with low number of ratings (< 60) unlike Jøsang's belief model. However, with increasing number of ratings, our model considers the confidence of the community and converges to true QoI value.

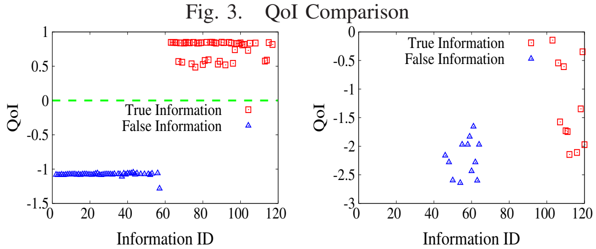
Fig. 3(b) compares the QoI achieved by $W2Q$ against Jøsang's belief model for true published information. It is noteworthy that in $W2Q$, the QoI converges to the true value only after gaining a sufficient support from the community, whereas in Jøsang's belief model, that support (or community confidence) does not matter.

3) QoI Analysis: Fig. 4(a) shows that $W2Q$ is able to efficiently classify true and false published information. A true information may end up having low QoI in scenarios with very few ratings (i.e., low community confidence) as shown in Fig.



(a) False Information (b) True Information

Fig. 3. QoI Comparison



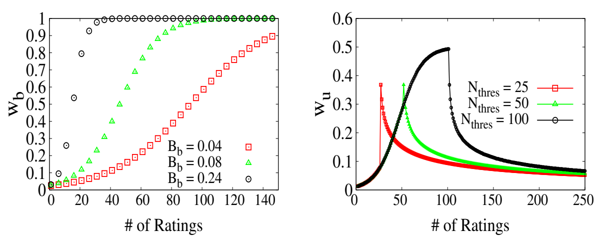
(a) (b)

Fig. 4. Classification: (a) Normal Ratings, (b) Very Low Ratings

4(b). This is because of the service provider's conservative approach. Thus, $W2Q$ takes both fraction of positive support and community confidence to evaluate QoI.

4) Decision Parameter Analysis: In this section, we discuss how the service provider may judiciously choose the suitable values for important parameters: B_b, B_u, and N_{thres}.

Effect of B_b: Fig. 5(a), shows the effect of B_b that controls the number of ratings N, required to attain the maximum possible value of w_b. For example, if the concerned area is inherently crowded and higher number of ratings are expected, then B_b should be kept low such that w_b attains maximum value after a sufficient number of ratings are received. However, if the system is less conservative, it can have low B_b. Similar is the case with B_u.



(a) (b)

Fig. 5. (a) Effect of B_b; (b) Effect of N_{thres}

Effect of N_{thres}: A small N_{thres} would prevent w_u, to reach its maximum value, before the uncertainty discounting starts as depicted in Fig. 5(b). Selection of an ideal N_{thres} depends on the application type and the service provider's risk attitude which is an open issue.

VI. Conclusion

In this work, we propose a novel model, called $W2Q$, to evaluate the QoI of published information in social sensing. $W2Q$ incorporates the total number of ratings, proportion of positive ratings and uncertain ratings. The resultant QoI enables the application provider to decide whether to persist with a published information or not, taking suitable actions to thwart the deterioration of the information quality, while being more resilient to dishonest raters and null invariance. As a part of the future work, we intend to propose a reputation model which estimates the reputation score of the sensing agents based on their quality of participation. Such score will enable the application provider to segregate honest from rogue agents so that fair incentives and service levels can be provided.

Acknowledgment

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