ENHANCING PUBLIC REPUTATION SYSTEMS: TRUST SCALING TO MITIGATE VOTER SUBJECTIVITY

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ABSTRACT

In the digital age, the reliability of public reputation systems is increasingly challenged by the subjectivity of voter assessments. This paper presents a novel public reputation estimation method that leverages a scaling trust framework to mitigate the influence of individual biases and enhance the accuracy of reputation scores. We propose a scaling mechanism that adjusts the weight of each voter's input according to their trustworthiness, thereby reducing the impact of outlier opinions and fostering a more balanced representation of public sentiment. The experiment results demonstrate that our method significantly improves the robustness and fairness of reputation estimations compared to traditional models.

KEYWORDS

Reputation; Trust; Voter subjectivity; E-commerce

1. INTRODUCTION

The relationship between personal trust and public reputation has been a subject of research for many years (Asiri and Alshamrani [1], Corbitt et al. [2], Dai and Cui [3], Falahat et al. [4], Jeon et al. [5], Kas et al. [6], Kusuma et al. [7], Oghazi et al. [8], Zloteanu et al. [9]). Understanding how individual trust translates into collective reputation has significant implications, especially in contexts where decisions are made based on aggregated opinions, such as in online marketplaces, social platforms, and review sites. Traditionally, personal trust has been the cornerstone of reputation systems, with the assumption that if many individuals trust a product, service, or person, this trust will be reflected in a strong public reputation.

In the digital age, online platforms increasingly rely on reputation systems to facilitate user interactions, foster trust, and enhance overall engagement. With the rapid growth of ecommerce and digital interactions, the need for reliable public reputation systems has become more critical than ever. Consumers increasingly rely on these systems to make informed decisions, and businesses depend on them to build and maintain trust with their customers. In response, numerous trust-based public reputation models have been proposed, aiming to harness individual trust assessments to create a collective reputation score as a kind of representative of the quality and reliability of a given service. For instances, Xiong and Liu [10] present PeerTrust - a coherent adaptive trust model for quantifying and comparing the trustworthiness of peers based on a transaction-based feedback system. Wang and Vassileva [11] propose a trust model which is based on Bayesian network and a reputation model which is based on recommendations in peer-to-peer networks. Balaji et al. [12] proposed a reputation model which is calculated from users feedbacks by using algorithm for weights and ratings computation. Goncalves et al. [13] proposed

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two major approaches which are based on public and permissioned blockchains. In the work of Nguyen and colleges ([14], [15], [16], [17], [18], [19]), trust (and also distrust) is estimated from the interactions in the past (experience trust), or from the evaluation of others (reputation), or from both types of trust above. Jain and Singh [20] proposed a trust model based on opinion dynamics temporal network. Lee et al. [21] presented a trust model based on the judgment of buyers. Priya and Ponmagal [22] presented a trust model based on reputation. You et al. [23] also presented trust model based on reputation.

However, despite their widespread adoption, trust-based public reputation models face a significant challenge: they are inherently dependent on the subjectivity of voters. Differences in experience and/or subjectivity among voters can lead to reputation scores that are not fully representative of the actual trustworthiness of the entity being evaluated (Bufacchi [24], Dawson [25], Gherghina and Marian [26], Moon et al. [27], Kusche [28]). This subjectivity can introduce inconsistencies and inaccuracies, undermining the effectiveness of public reputation systems and reducing their reliability.

To address this challenge, this paper proposes a novel approach: a scaling trust-based public reputation model designed to mitigate voter subjectivity. Our method introduces a scaling mechanism that adjusts the influence of each voter's input based on their trustworthiness, as determined by their past voting behaviour. By scaling the individual votes according to the consistency and reliability of the voter's previous assessments, our model aims to reduce the impact of biased or anomalous opinions and produce a more accurate and balanced public reputation score.

This paper presents scaling trust mechanism in reputation systems. In which, the scaling trust can improve the accuracy and fairness of reputation scores, particularly in environments where voter subjectivity poses a significant challenge. Through this work, we aim to contribute to the on-going development of more reliable and trustworthy public reputation systems in the digital age. The paper is organized as follows: Section 2 presents the similarity model. Section 3 presents some experiments to evaluate the proposed model in some considered factors. Section 4 is the conclusion and perspectives.

2. TRUST SCALING MODEL

Without loss of generality, we assume that:

- A public community could be considered as a multi-agent system, in which, member agents are called agent *i*, agent *j*.
- There is possibly some transactions between agent *i* and agent *j* in the community. After each transaction *k*, agent *i* may vote the service quality of agent *j*: t^k_{ij} is called the real trust of agent *i* on the agent *j* over the transaction *k*. Note that, t^k_{ij} may differ from t^k_{ji} for several $i \neq j$.
- Let's [MIN,MAX] is the normalized interval value of transaction trust, therefore $t^k_{ij} \in$ [MIN,MAX] for $\forall$i, j, k.
- Let's t^{min}_i is the minimal transaction trust value voted by the agent *i*:

$$t^{min}_i = \min\{t^k_{ij} \mid \forall j,k\} \tag{1}$$

- Let's t^{max}_i is the maximal transaction trust value voted by the agent *i*:

$$t^{max}_i = \max\{ t^k_{ij} \mid \forall j,k \} \tag{2}$$

- The subjectivity difference of a voter i regarding the normalized interval [MIN,MAX] is:

$$d_i = \frac{\max(\left|t_i^{min} - MIN\right|, \left|t_i^{max} - MAX\right|)}{MAX} \tag{3}$$

The higher this value is, the more different the agent's subjectivity is.

- The *Scaled trust* of transaction *k* voted by agent *i* for agent *j* is estimated as follow:

$$st_{ij}^k = \begin{cases} MIN + \frac{\left(t_{ij}^k - MIN\right) * (MAX - MIN)}{(t_i^{max} - t_i^{min})} \ if \ d_i \geq \theta \\ t_{ij}^k \ if \ d_i < \theta \end{cases} \tag{4}$$

where θ is a subjectivity difference threshold. If the subjectivity difference of a voter is higher than this threshold, then the scaling of original trust is needed; otherwise, the classical (without scaling) is applied to calculate the transaction trust of the voter. This subjectivity difference threshold is possibly considered as a parameter which may influence on the model. It is thus experimented in the evaluation section.

- The public reputation of agent j is thus estimated as the mean of all scaled trust voted for agent j:

$$r_j = \frac{1}{N*M} \sum_{i=1}^{N} \sum_{k=1}^{M} st_{ij}^k \tag{5}$$

The more this public reputation is closed to the MAX value, the better the agent *j*.

3. EVALUATION

This section presents the evaluation of the proposed model by testing some sensitive parameters used in the model such as the best threshold of θ, compare to the traditional reputation, and testing in the case of limited number of transaction.

3.1. Simulated System Setup

In order to evaluate the public reputation by using the proposed scaled trust, we created a simulated e-commerce system on the GAMA platform[29]. In this system:

- There are many seller agents who sell some products and many buyer agents who buy some products.
- A product has a real utility value for buyer.
- A transaction occurs when a buyer agent decides to buy a product from a chosen seller agent. The buyer agent has the right to evaluate the transaction quality (also the product quality - based on the real utility value of the product) of the seller agent after each transaction between them. The evaluated value is also called transaction trust.
- The public reputation of a seller agent is estimated from all the transaction trust evaluated by all of its clients. This public reputation is published for all buyer agents in the system.
- Before making a transaction, a buyer agent chooses the best seller agent based on their public reputation: The seller agent with the highest public reputation will be chosen.

- The higher the real value of bought products that buyer agents obtain, the more efficient the public reputation method is.

The used value of parameters in the system is listed in the Table 1.

Table 1. Simulated system configuration

Parameters	Value
Number of seller	1000
Number of buyer	1000
Average number of product/seller	500
Average number of bought product/buyer	50
[MIN, MAX]	[0,5]

3.2. Experiment 1: The best threshold θ

This experiment is conducted to determine the optimal value for the subjectivity difference threshold (θ) by testing various values of this parameter.

3.2.1. Scenario

The experimental scenario is structured as follows:

- Iteration across θ values: The experiment is repeated for each of the following subjectivity difference threshold (θ) values: 0%, 5%, 10%, 15%, 20%, 25%, 30%, 35%, 40%, 45%, 50%:

  – For each specified value of θ, the simulated system, as described in Section 3.1, is executed.
  – Single buyer utility calculation: During the simulation, observe and compute the mean real utility value of all products purchased by each buyer agent. This value is referred to as the single buyer utility value.
  – Overall buyer utility calculation: Next, calculate the average of the single buyer utility values across all buyer agents in the system, normalized as a percentage. This is called *the overall buyer utility value*.
  – Repetition and averaging: The above steps are repeated 50 times for each given value of θ. The mean of *the overall buyer utility values* from these 50 simulation runs is then calculated, resulting in *the buyer utility value* for the specific value of θ.

- Comparison and selection of optimal θ: Finally, *the buyer utility values* for all the tested θ values are compared. The θ value that yields the highest *buyer utility value* is identified as the optimal subjectivity difference threshold. This optimal value will be utilized in subsequent experiments.

3.2.2. Results

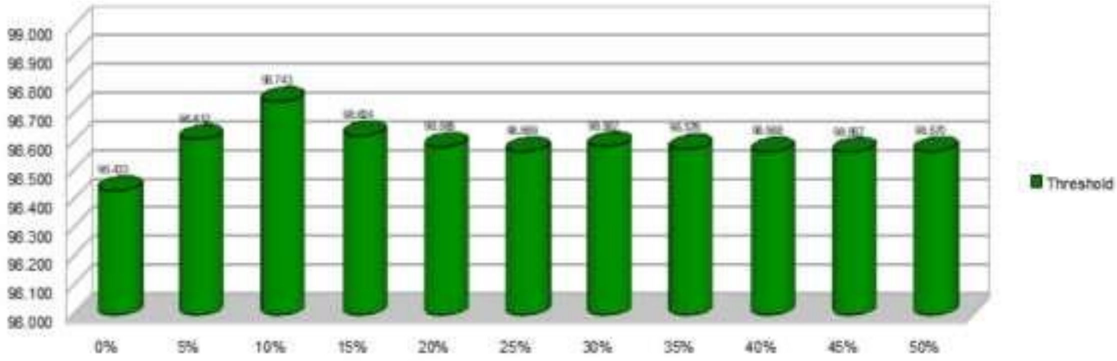

Figure 1. Variation of buyer utility value with several subjectivity difference threshold θ

The results are illustrated in Figure 1. They show that the buyer's utility value reaches its peak when the subjectivity difference threshold (θ) is set at 10%. Beyond this point, the utility value starts to decline. Specifically, the maximum buyer utility value observed is 96.74% at θ = 10%. This indicates that a 10% threshold is optimal for maximizing buyer utility. Consequently, this threshold will be applied in the subsequent experiments to ensure the most favorable outcomes.

3.3. Experiment 2: Compare to Classical Reputation

This experiment is conducted to evaluate the effectiveness of the proposed model, which incorporates public reputation with scaled trust, in comparison to the traditional public reputation model that does not include scaled trust. The comparison is performed across various system configurations, each with different ratios of anomaly subjectivity buyer agent.

3.3.1. Scenario

The experiment follows this scenario:

- Iteration across anomaly subjectivity ratios: The experiment is conducted for each ratio of anomaly subjectivity among buyer agents: 0%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, For each ratio, the following steps are repeated:

  – System initialization: Initialize the system with the specified ratio of anomaly subjectivity buyer agent.
  – System execution with two reputation methods:

- Classical method (without scaling trust): In this method, the reputation of a seller agent is calculated directly as the mean of all original transaction trust values given by buyer agents who purchased products from that seller.

This is done using the formula:

$$r_j = \frac{1}{N*M}\sum_{i=1}^{N}\sum_{k=1}^{M} t_{ij}^{k} \qquad (6)$$

- Proposed method (with scaling trust): In this method, the reputation of a seller agent is also calculated using the formula from Equation 5. However, this time it incorporates scaling trust, with the subjectivity difference threshold (θ) set at 10%, as determined to be the optimal value in the first experiment.

- Single buyer utility calculation: During the simulation, observe and compute the mean real utility value of all products purchased by each buyer agent. This value is referred to as the single buyer utility value.
- Overall buyer utility calculation: Next, calculate the average of the single buyer utility values across all buyer agents in the system, normalized as a percentage. This is called *the overall buyer utility value*.
- Repetition and averaging: The above steps are repeated 50 times for each given value of anomaly subjectivity ratio. The mean of the *overall buyer utility values* from these 50 simulation runs is then calculated, resulting in the *buyer utility value* for the specific value of anomaly subjectivity ratio.

• Comparison of methods: Finally, the *buyer utility values* obtained from both the classical and proposed methods are compared across all tested ratios of anomaly subjectivity among buyer agents. For any given ratio, the method that produces the higher *buyer utility value* is considered the superior approach.

3.3.2. Results

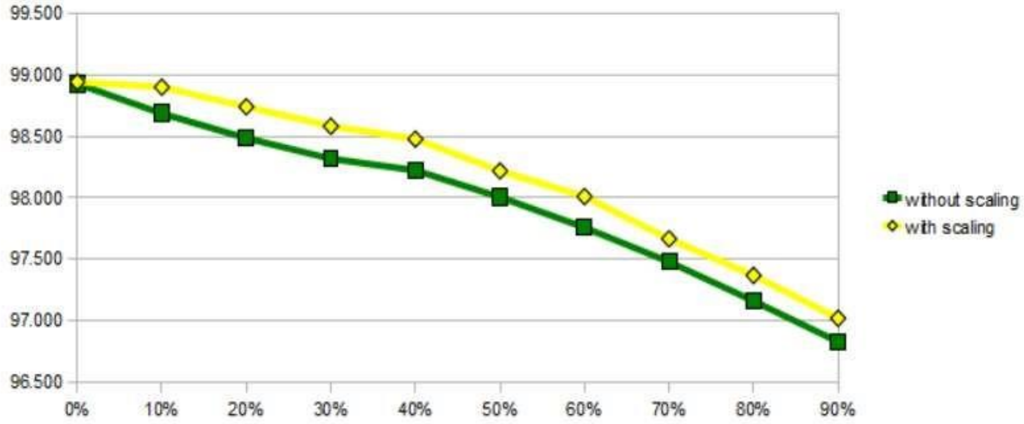

Figure 2. Comparison the buyer utility value between two methods (withoutand with scaling trust) on many ratio of anomaly subjectivity buyer agent

The results are illustrated in Figure 2. They reveal that when there is 0% anomaly subjectivity among buyer agents in the system, the buyer utility values obtained from both methods show no significant difference. However, as soon as the anomaly subjectivity ratio reaches 10% or higher, the buyer utility value for the method incorporating scaling trust consistently exceeds that of the method without scaling trust. This trend indicates that the proposed method becomes increasingly advantageous as the proportion of anomaly subjectivity among buyer agents increases.

3.4. Experiment 3: Comparison when there is Few Data

Since reputation depends on the past experiences of voters, it may not be accurate if there have been too few transactions involving those voters. Therefore, the objective of this experiment is to evaluate the proposed model compared to the classical public reputation model (without scaled trust) under conditions where there is limited transaction trust data from voters in the past.

3.4.1. Scenario

The experiment is taken with the following scenario:

- Iteration across average transactions per buyer: The experiment is repeated for cases where each buyer has, on average, purchased 1, 2, 3, 4, 5, 6, 7, 8, 9, or 10 products. This means that the system contains, on average, the corresponding number of transaction trust records for each buyer.

  – System initialization: Initialize the system with the specified ratio of anomaly subjectivity buyer agent.
  – System execution with two reputation methods:

- Classical method (without scaling trust): In this method, the reputation of a seller agent is calculated directly as the mean of all original transaction trust values given by buyer agents who purchased products from that seller. This is done using the formula 6.
- Proposed method (with scaling trust): In this method, the reputation of a seller agent is also calculated using the formula from Equation 5. However, this time it incorporates scaling trust, with the subjectivity difference threshold (θ) set at 10%, as determined to be the optimal value in the first experiment.

  – Single buyer utility calculation: During the simulation, observe and compute the mean real utility value of all products purchased by each buyer agent. This value is referred to as the single buyer utility value.
  – Overall buyer utility calculation: Next, calculate the average of the single buyer utility values across all buyer agents in the system, normalized as a percentage. This is called *the overall buyer utility value*.
  – Repetition and averaging: The above steps are repeated 50 times for each given number of transaction trust. The mean of *the overall buyer utility values* from these 50 simulation runs is then calculated, resulting in *the buyer utility value* for the specific number of transaction trust.

- Comparison of methods: Finally, the *buyer utility values* obtained from both the classical and proposed methods are compared across all tested number of transaction trust. For any given ratio, the method that produces the higher *buyer utility value* is considered the superior approach.

3.4.2. Results

The results are shown in Figure 3. They reveal that when the average number of transaction trust records per buyer is fewer than 3, the classical reputation method yields a higher buyer utility value than the proposed method. However, when the average number of transaction trusts exceeds 3, the buyer utility value for the method incorporating scaling trust consistently surpasses that of the classical method.

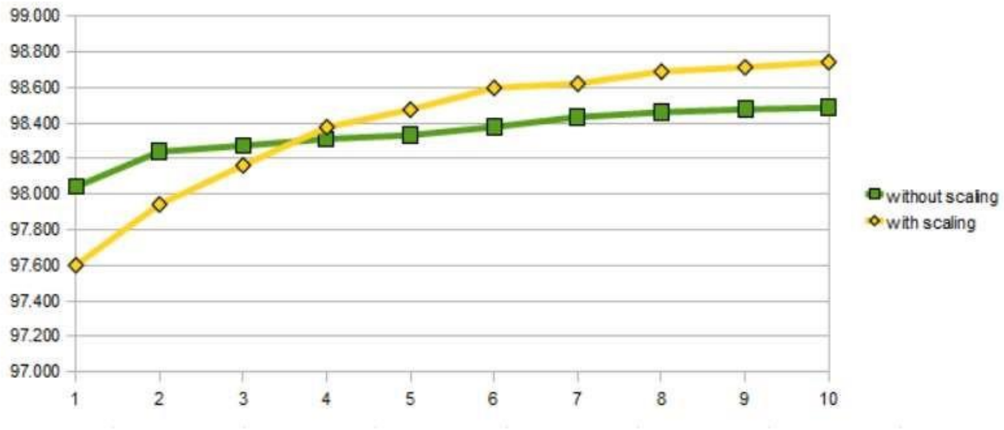

Figure 3.Comparison the buyer utility value between two methods (withoutand with scaling trust) on different small value of transaction trust

In summary, the proposed model could perform similarly to, or less effectively than, the classical public reputation method when there are no anomaly subjectivity voters in the system or there is a limited amount of transaction trust data from voters. However, in scenarios where anomaly subjectivity voters are present or there are sufficient amount of transaction trust data, the public reputation method with scaling trust proves to be more reliable. It offers better support for voters in identifying the most trustworthy partners.

4. CONCLUSIONS

This paper proposes scaling trust framework which offers a significant advancement in enhancing the accuracy and fairness of public reputation systems in the face of subjective voter assessments. By dynamically adjusting the weight of voter inputs based on trustworthiness, our method effectively minimizes the influence of biased or outlier opinions. The results from experiments validate the robustness of this approach, demonstrating its superiority over traditional models in producing more reliable and equitable reputation scores.

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