A Blockchain-based trust model for crowd environments.

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ABSTRACT

Nowadays, social media has become an important platform for people to share information and opinions. More and more businesses owners and individual users rely on information shared on social media and contributed by the crowd for product promotion, decision making, etc. However, it is difficult to evaluate the trustworthiness of such information effectively as the open environment allows all people with different backgrounds and expertise to contribute. Furthermore, it gives chances for malicious users or astroturfers who pursue profits by giving fake reviews or plausible answers, and those who want to build up their business's reputation without improving quality of good or service. For solving this challenging problem, the paper considers trust as a key element and define it in the expert-based context. Then we propose a Blockchain-based trust model for information sharing in crowd environments. The proposed model uses a weighted consensus mechanism to infer the trustworthiness of shared information basing on reviews from the crowd and defines the accuracy of an agent as the ratio of his winning reviews to his total reviews. The model can reward agents effectively equivalent to his winning reviews. Experimental results show that the proposed model has higher accuracy in defining the trustworthiness of information and obtains better Collective Intelligence than existing models.

CCS CONCEPTS

• **Information systems → Content ranking**; **Social recommendation**; **Crowdsourcing**; **Trust**; **Incentive schemes**; **Reputation systems**; *Social networks.*

KEYWORDS

crowdsourcing, expert-based context, consensus, trustworthiness

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1 INTRODUCTION

Nowadays, social media plays a pivot role in most people's activities in all areas such as business, recreation, hospitality, education, etc. People of all ages rely on these applications to communicate and interact with each other freely and independently. Such platforms are described as crowd environments [2]. It is estimated that about 80% people in the world using these applications such as Google Map, Instagram, Facebook, and YouTube to plan their business or daily tasks without depending on any central authority[1]. There are two possible reasons for the popularity of such social applications. First, people may find countless of useful information or contents which help their daily tasks or business operations. Second, such existing environments give them chances to build their reputations through rewarding mechanisms for their interactions with each other. Later on, they use reputations for different benefits such as classifying levels in Google review, exchanging gifts in Gmarket[2], and converting them to cryptocurrency in the future as Facebook's announcement this year[3]. Therefore, the trustworthiness of shared contents and reputation of participants play important roles in such platforms. The following limitations could discourage people from joining this kind of crowd environment.

In general, a massive amount of information is published in a crowd environment where each individual has his opinion, background, and experience. Therefore, it is difficult to have an effective scale for the trustworthiness of content as an idea could be true for this person in a specific field but not true for the others in other fields. Existing platforms such as a content trust learning algorithm proposed by Wang [9] has a mechanism to eliminate the malicious contents. However, this approach does not cover the multi-dimensional aspects of the content. Similarly, more research works can be seen in [7] which reviews various aspects of fake detection approaches which are classified by three categories including content-based defence, network structure, and hybrid techniques, but none of them considers the trustworthiness of information in different contexts. As a result, the trustworthiness of contents in existing social networks naturally is based on reviews and "likes" provided by the crowd. It makes the economy for astroturfing or fake reviews flourish [7] as unsuitable individuals tend to contribute more feedbacks than the experts. For example, all restaurants in Google Maps have ratings according to their consumers' voting and comments. Those with more reviews and good comments dominate the others and increase their sales. Thus, some business owners put efforts on buying good reviews from astroturfers to attract consumers rather than improving the service quality.

In most existing trust models [10], the trust value is inferred or calculated from opinions of the whole community. However, nobody knows everything in the world; such community-based trust will not be true if inexpert and expert people are treated as

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[1] https://www.business2community.com/social-media/2019-social-media-trends-statistics-02156179
[2] http://global.gmarket.co.kr/Home/Main
[3] https://www.forbes.com/sites/eladnatanson/2019/01/02/facebook-cryptocurrency-and-the-future-of-mobile-commerce

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the same. Thus, existing approaches cannot effectively evaluate the information on social media. Furthermore, conventional reputation models [4] reward reputations to participants basing on their interactions' feedbacks, which are too narrow and subjective, then creates more advantages for malicious agents to cooperate. Modern existing blockchain-based reputation models such as DREP[4] and Backfeed[5] have some efforts to apply blockchain theory on reputation rewarding mechanisms which objectively encourage all individuals in a crowd environment to participate and reward them according to the trustworthiness of their interactions. However, DREP does not consider the arrival time of agents' interactions, while the trustworthiness of contents always changes over time. In the Backfeed model, time is integrated into the reward formulation to attract participants to join in early time. However, this model prioritizes their proactivity than trustworthiness, and it seems to reward more for proactivity than trustworthiness. Hence, existing models can not solve the problems of expert-based trust and astroturfing effectively. Thus, an effective trust model highly demands to assure quality information and a reasonable reputation for participants in the crowd environment. This research aims to solve the problem of expert-based trust and to prevent astroturfing by applying crowdsourcing in trust and reputation models. Below are the main contributions:

(1) We propose a blockchain-based trust model named TrustBF where evaluators in the crowd are from different expertise fields. In this model, we apply crowdsourcing to collect reviews from expertized evaluators or real consumers. We present a consensus mechanism to evaluate the reviews and weigh them according to expertise, experience, and arrival time of evaluators. After that, we calculate the trustworthiness of the reviews from weighted evaluators' answers. Thus it effectively presents for the opinion of both community and experts in its field contemporarily.
(2) In the weighted consensus algorithm of TrustBF, we also define a deposit reputation function, and rewarding reputation formulas which depend on acting behaviours of evaluators. These rewards of reputation partly create motivation for evaluators to join the system seriously.
(3) We define Accuracy (ACC) and Collective Intelligence Factor (CI_f) to compare the accuracy and effectiveness of our proposed model with existing approaches in crowd environments. We conduct experiments with data sets from Google Review, and we compare the results with data on Zomato as a benchmark.

The rest of this paper is organized as follows. Section 2 presents related works. Section 3 describes the proposed approach Trust BF. Section 4 defines accuracy measurements for the proposed model. In Section 5, experimental results are presented and analyzed. Finally, Section 6 is the conclusion.

2 RELATED WORKS

There are various definitions of trust in different fields [10] [4]. Trust is the belief that an entity is a good quality or capable of acting reliability in a specialized extent, which is considered by relevant experts at a given time. The definition highlights two main characteristics of trust that we want to explore. First, trust is not a general belief of the whole community about an entity but a judgment of a group of experts or people who are qualified or well-knowledgeable and passionate about it. Second, trust depends on time. There have been many types of research on this concept. However, they have not been discovered completely. For example, WikiTrust [1] in Wikipedia uses the revision through time to evaluate the trustworthiness of the content. The trust increases when the content is preserved in a longer time. Other methods use time exponential function with discount factors to forecast the trust [10] [4]. It is not true in many cases when there are few interactions, and the content would be obsoleted. Therefore, the goals of this research are to focus on the trustworthiness of an entity evaluated by a group of experts (expert-based trust) rather than on a general trust of the whole community (community-based trust) on this entity in crowd environments.

User-driven trust and Content-driven trust Generally, there have been many trust and reputation models to address these above problems mentioned in the previous paragraph [10]. Most of these models are user-driven trust models, which are based on users rating contribution of others. Good examples are trust models in multi-agent systems in which trust is considered as an important element to initiate agents' interaction [8]. It is evident that some trust models can increase the trustworthiness of a distributed system such as CrowdTrust in [10] for the crowdsourcing environment. However, in most existing models, all participants in the crowd are treated similarly because the models do not have expert knowledge of the content of contributions. On the other hand, some approaches such as TruthFinder and WikiTrust in Wikipedia [1] use content-driven trust models to manage the trustworthiness of content and reputation of contributors. A major advantage of such models is that they do not rely on users' feedback, and trustworthiness is built directly from the content. However, as Adler [1] stated, content-driven approaches are less accurate than user-driven models because the content could be modified or even removed by the contributors.

Blockchain-based trust and reputation models in crowdsourcing environment. The basic theory of blockchain is the consensus algorithm and data storage as a chain of blocks. In these trust models, a block is reviewed result of evaluators on a service such as DREP and Backfeed [5].

In Backfeed [5], a consensus mechanism is a process to check and confirm the validity of a transaction or service before adding it to a block in the blockchain with the assumption that a block contains only one transaction. Namely, when an evaluator first comes to the loop, he loses some reputation scores as a deposit cost calculated from his current reputation scores and arrival orders. However, he will obtain a higher reputation in later steps when more evaluators come to vote with the same value. In case the later evaluators claim different values, the reputation of this evaluator remains constant. Finally, at the end of the process, it is inappropriate for this evaluator to hold a greater reputation score. In addition, the expertise of contributions and the trustworthiness of evaluators are not considered in the model and the coming order of evaluators dominate the trustworthiness. Thus, this model does not effectively solve the problem of expert-based trust in the crowd of evaluators.

[4]https://www.drep.org
[5]http://backfeed.cc

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We adopt the advantages of both user-driven and content-driven trust models and propose a blockchain-based trust model, which uses the evaluators' feedbacks as input for a weighted consensus mechanism. We calculate the weights from the relationship between contributions' contents and evaluators' expertise. In the proposed model, the trustworthiness of contents is evaluated by a weighted consensus mechanism.

3 TRUSTBF: A BLOCKCHAIN-BASED TRUST MODEL

In this research, we consider a crowd system as an MAS. It is typically to define multi-agent systems as a computer system including multiple intelligent agents interacting with each other, and an agent is a software agent [4]. This study considers an agent as a human or human-agent team. As we presented in Section 1, an effective trust model highly demands to assure a good quality of service and reputation for participants in crowd environments. Namely, service providers need an evaluation process from the community to approve his QoS. However, consumers may have different trust levels in different fields of goods and services. When he has to deal with goods and services which are not interesting to him, he may review negatively. Therefore, we propose TrustBF, which is based on crowdsourcing and blockchain consensus mechanism to address this problem. We define basic definitions as below.

Definition 3.1. **A consumer agent** $a_i, (a_i \in A)$ is defined as a vertex in a social network $G = (A, L, E)$, where $A = \{a_1, ..., a_n\}$ represents for a set of consumers, $L = \{l_1, ..., l_m\}$ represents for a set of services (see definition 3.2), and $E = \{e_{ij} = 1 | 1 \le i \le n, 1 \le j \le m\}$ represents for a set of edges with $i, j \in N^+$, $a_i \in A, l_j \in L$. a_i is a three-tuple $a_i = \{x_{a_i}, r_{a_i}, acc_{a_i}\}$ where $x_{a_i} = \{x_{iz} \in [0, 1] | 1 \le i \le n, 1 \le z \le h\}$ represents for the expertise of agent a_i in a set of fields $Z = \{1, ..., h\}$, r_{a_i} denotes the reputation score of agent a_i and is updated by Equation 4. acc_{a_i} represents the accuracy of agent a_i and defined by Equation 1.

$$acc_i = \frac{\sum_{e_{ij} \in E} \delta_{ij}}{\sum_{e_{ij} \in E} |e_{ij}|} \tag{1}$$

with δ_{ij} is the successful factor (see definition 3.6).

Definition 3.2. **A service** $l_j, (l_j \in L)$ is defined as a vertex in network G. l_j has a set of consumers $\Theta(l_j)$. If agent a_i is the consumer of service l_j, then $e_{ij} \in E, a_i \in \Theta(l_j)$. l_j has a set of reviews $V(l_j)$ with $V(l_j) = \{v_{ij} \in [0, 1] | a_i \in \Theta(l_j)\}$, v_{ij} is a review value of agent a_i on l_j. l_j is a two-tuple with $l_j = \{y_{l_j}, tc_{l_j}\}$. y_{l_j} is a set of proximities with $y_{l_j} = \{y_{jz} \in [0, 1] | \sum_{z=1}^{h} y_{jz} = 1\}$, y_{jz} is the proximity of l_j to field z. tc_{l_j} is the content-trust of l_j (see definition 3.5).

Definition 3.3. **Context** $\omega_{l_j}(p)$ demonstrates a review process for l_j in a time period p. The context of l_j is denoted by using a eight-tuple, $\omega_{l_j}(p) = \{Tr_{l_j}, T_{l_j}, C_{l_j}, \Theta(l_j), V_{l_j}, \Delta_{l_j}, RA_{l_i}, CI_{fj}\}$, where $Tr_{l_j} = \{tr_{ij} \in [0, 1] | 1 \le i \le n, a_i \in \Theta(l_j)\}$ is the set of expert-trusts (see definition 3.4), $T_{l_j} = \{t_{ij} \in R^+ | a_i \in \Theta(l_j)\}$ denotes the set of arrival time of agents, $C_{l_j} = \{C_{ij} \in R^+ | a_i \in \Theta(l_j)\}$ denotes the set of deposit reputations and is defined by Equation.3, $RA_{l_j} = \{RA_{ij} \in [0, 1] | a_i \in \Theta(l_j)\}$ denotes the set of reputation rewards of consumer agents and is defined by Equation 7, and CI_{fj} is Collective Intelligence factor (see definition 4.2).

Definition 3.4. **Expert-trust** $tr_{ij} \in Tr_{l_j}$ representing the expertise and background of an agent a_i about a service l_j is calculated as $tr_{ij} = x_{a_i} y_{l_j}$ with $a_i \in \Theta(l_j)$.

Definition 3.5. **Content-trust** tc_{l_j} denotes the trustworthiness of a service l_j and is calculated as below.

$$tc_{l_j} = q \frac{\sum_{a_i \in \Theta l_j} \frac{tr_{ij} v_{ij}}{e^{t_{ij} - t_p}}}{\sum_{a_i \in \Theta l_j} tr_{ij}} \tag{2}$$

$t_{ij} \in T_{l_j}$ and $t_p \in T^p$ (see definition 3.7) is the end of a time period for the review of service l_j, and q is an adjustable parameter.

Definition 3.6. **Successful factor** $\delta_{ij} \in \Delta_{l_j}$ denotes the success of a review after going through the weighted consensus mechanism. The set of successful factors $\Delta_{l_j} = \{\delta_{ij} = \{1 | (v_{ij} \le tc_{l_j} \le \eta) \vee (v_{ij} \ge tc_{l_j} \ge \eta), 0\}, a_i \in \Theta(l_j)\}$. with η is a consensus ratio and a given constant.

Definition 3.7. **Period ending time** $t_p \in T^p$ denotes the ending time of a period p when the model ends one loop of review process for l_j. The set of period ending times is $T^p = \{t_p = p \times \alpha | p \in N^+\}$ with α is a given constant of time.

From these above definitions, we propose a blockchain-based TrustBF model including four steps as shown in Figure 1: (1) a service provider performs a service, (2) the provider sends review requests to his consumers every time period, (3) selected agents send answers to weighted consensus mechanism (WCM) which leverages the blockchain technique to control the reviews in the time period, (4) WCM notifies results and distributes rewarding reputations every time period. This process ends when the provider stops his service or it reaches a terminated period time. This proposed model can address the problem of fake reviews by getting help from the crowd of consumers through a blockchain-based consensus mechanism. It also uses agents' expertise and provided evidence to weight their answers to get consensus and reward reputations.

3.0.1 Weighted consensus mechanism. Existing platforms DREP and Backfeed open calls for agents and give the same weights for their evaluations in the consensus loops. These existing approaches do not solve the problem of expert-based trust as the trustworthiness of a service in different fields cannot similarly be evaluated by the agents. We propose a weight which is equivalent to the belief or trustworthiness of an agent about a specific service and a blockchain-based validation process to evaluate the trustworthiness.

Algorithm 1 demonstrates the weighted consensus mechanism with blockchain-based validation process in TrustBF. The deposit of reputations depends on the current reputations and arrival order of agents. The proposed protocol uses these two elements in the deposit function. However, to solve the above problem, we add the expert-trust as a weight to the formula. This weight prioritizes expert agents. Thus, it reduces the chance of malicious evaluators and significantly eliminates the astroturfers. The deposit reputations function is defined as below:

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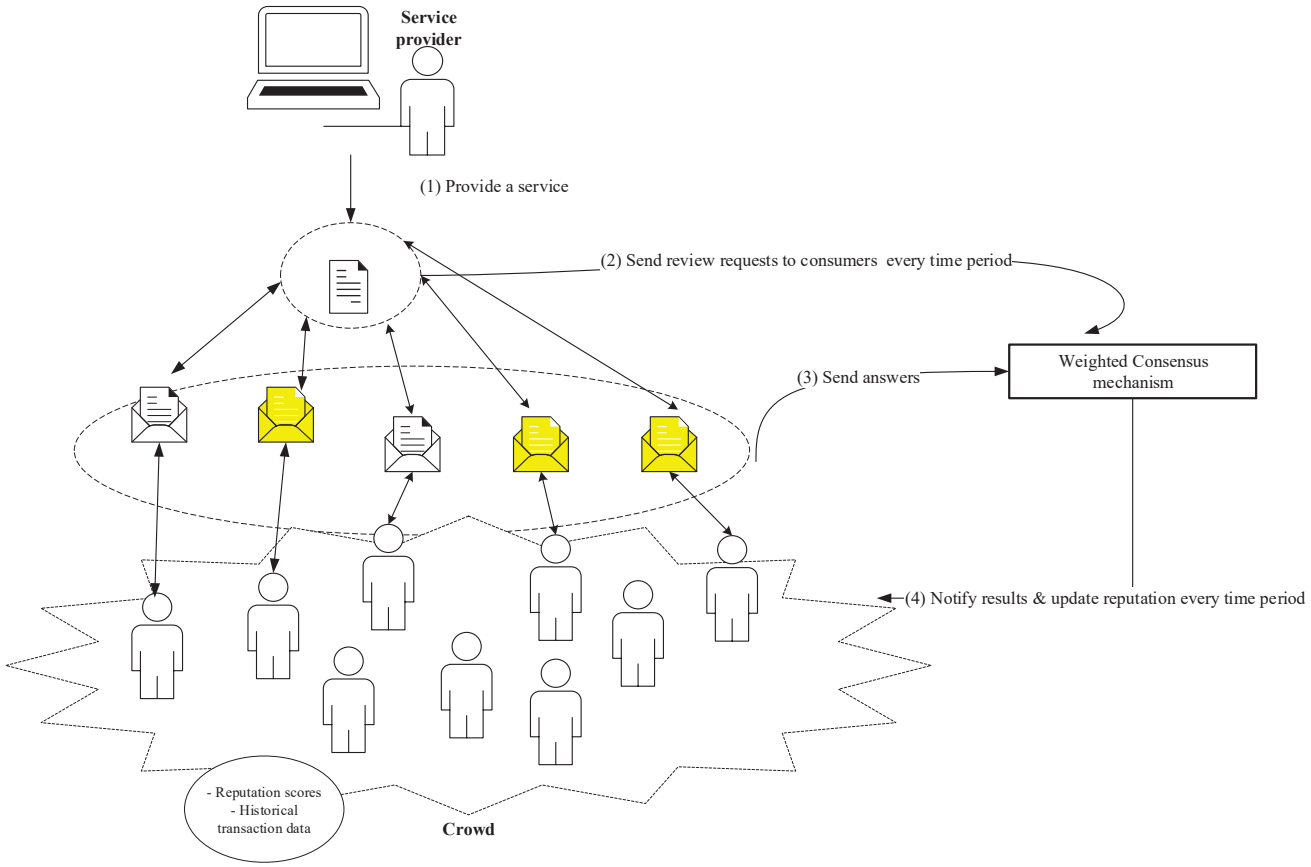


Figure 1: Architecture of TrustBF model

$$C_{ij} = s \times r_{a_i} \times \left(1 - \left(\frac{tr_{ij} \times r_{ij}}{\sum_{a_i \in \Theta(l_j)} r_{a_i}}\right)^{\gamma}\right) \quad (3)$$

Where s and γ are adjustable parameters.

In Backfeed [5], the reputations of agents are updated every time a new agent comes to the evaluation loop. TrustBF differently has a process to distribute reputations once in every time period p. Namely, at a given time period p, TrustBF modifies the reputations for agents who arrived before a_k by Equation 4. Another difference is that TrustBF updates reputations basing on the current reputations, arrival time and evidence or argument provided by agents.

Figure 2 generally demonstrates the block-chain based validation process. Namely, after one voting loop finishes and a block is confirmed, all evaluators will have new reputation scores, and the arrival time is very important to them. Specifically, evaluators come to the loop at a different time between t_s and t_e and their reputation scores change during this period. For instance, we observe an evaluator with an orange reputation line. When he first comes to the loop, he loses some reputation scores as deposit cost calculated from his current reputation scores and arrival time. However, he will obtain a higher reputation in later steps when more evaluators come to vote with the same value. In case the other evaluators claim different values, this evaluator remains his reputation constant. Finally, at the end of the process, this evaluator holds a greater reputation score.

Algorithm 1 Weighted consensus algorithm

```
1: procedure INPUT(G = (A, L, E))
2:     while a_i ∈ Θ(l_j) do
3:         while t_p ≤ t_p^terminated do
4:             Calculate C_ij ← Equation3
5:             Calculate tr_ij ← Equation3.4
6:             Calculate tc_j ← Equation2
7:             if v_ij ≤ tc_j ≤ η or v_ij ≥ tc_j ≥ η then
8:                 Update agent's reputation
9:         return r_{a_i}, tc_j
```

$$r_{a_i}^{(p)} = r_{a_i}^{(p-1)} + \delta_{ij} \times d \times tr_{ij} \times r_{a_k} \times \left(\frac{r_{a_i}^{(p-1)}}{\sum_{a_i \in \Theta l_j, a_i = a_k} a_i}\right) \quad (4)$$

A significant difference between Backfeed and TrustBF is the value of δ_{ij}. In TrustBF, δ_{ij} is equal to 1 if $v_{ij} \leq tc_j \leq \eta$ or $v_{ij} \geq$

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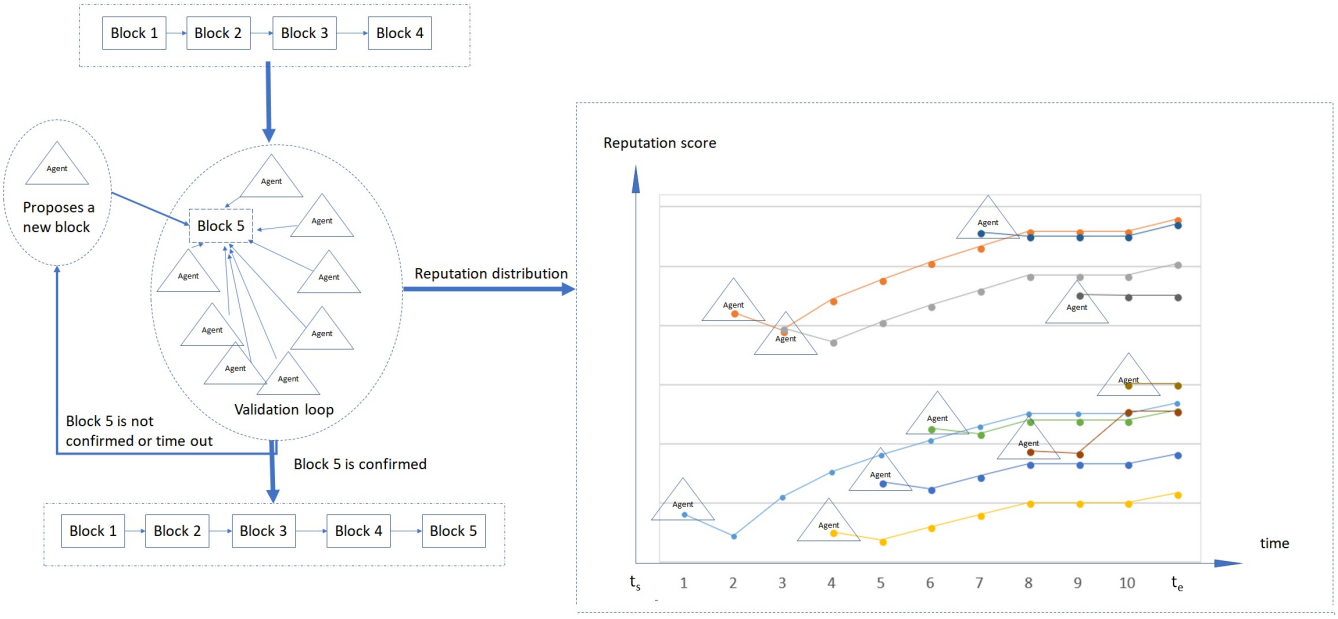


Figure 2: Blockchain-based validation process

$tc_j \geq \eta$, and 0 otherwise with η is a consensus ratio and a constant. In Backfeed, this value is 1 only if the a_i has the same value with current a_k even if a_k has a bad vote.

4 ACCURACY MEASUREMENT FOR THE PROPOSED MODEL

As mentioned in Section 1, existing platforms such as Facebook, Google Review, and Instagram calculate trustworthiness of service from reviews of consumers. This study defines the accuracy of these crowd environments by the differences in results between them and an expertise environment. For instance, in the hospitality field, including restaurants and espresso bars, Zomato is a famous and reliable application for people who are interested in cuisine. The reviews of restaurants on Zomato [6] are highly accurate. Hence, We calculate the accuracy as the ratio of review rate on a distributed platform (RR) and review rate on an expertise platform (RR*) such as Zomato. Namely, this paper considers the five-star rating from 1 to 5. Accordingly, review rate and accuracy of TrustBF should be defined as in Equation 5 and Equation 6 respectively.

$$RR_{TrustBF} = \frac{tc_j \times 5}{10} \tag{5}$$

$$ACC_{TrustBF} = \frac{RR_{TrustBF}}{RR^*} \tag{6}$$

In addition, this paper proposes a measurement called CI_f to evaluate the performance of TrustBF. Before CI_f is defined, some definitions are described below.

Definition 4.1. **Reputation reward** $RA_{ij} \in RA_{l_j}, a_i \in \Theta(l_j)$ is defined as the ratio of extra reputation scores obtained after rating to reputation scores before rating for l_j and is calculated in Equation 8. This study considers RA because of the following reasons. It is clear that each agent has a different reputation at all times. The higher the reputation an agent has, the higher the reputation scores he can obtain in the future review. If a 1000-reputation-score gains 10 scores, which does not mean that he is better than a 100-reputation-score who also gains 10 scores.

$$RA_{ij}^{(p)} = \frac{r_{a_i}^{(p)} - r_{a_i}^{(p-1)}}{r_{ij}^{(p-1)}} \times 100\% \tag{7}$$

Definition 4.2. **Collective Intelligence factor** $CI_f = \{CI_{fj}, 1 \leq j \leq m\}$ represents the reliability and effectiveness of a trust and reputation model in crowd environments. It is estimated by relationship between the accuracy of agents and their reputation rewards [3].

$$CI_f = \{correlation(acc_i, RA_{ij}) | a_i \in \Theta(l_j)\} \tag{8}$$

Any agent comes to the system with integrity and trustworthiness desires to achieve the deserved reward. RA is a worthy asset that all agents aspire to obtain. A good system will reward the right agents. Therefore, we use CI_f to assess how much a good trust and reputation model is. It is reasonable that the more trustworthy agent gains more RA and conversely.

5 EXPERIMENTS

We test the accuracy of TrustBF on real data sets of Google Maps and the efficiency of this model by simulation data and run it in Python. The objective is to know how much the improvement of this proposed TrustBF compared with existing trust and reputation models. The result is demonstrated below.

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5.1 Accuracy comparison between existing platforms and TrustBF

The real data sets from Google Map contain 10 profiles of 10 restaurants or espresso bars, which are equivalent to 10 services in Google Review of Google Maps. Each profile has a general review rate of a restaurant and a list of comments with a rating from different consumers. This study considers these comments as expertise, evidence or arguments of consumers or agents, and ratings are their reviews' values. Later on, we use TrustBF to calculate the content-trust of these ten restaurants and convert these results to review rates RRs. After that, we compare these RRs with review rate RRs* of these restaurants in a specialized application Zomato. The reason why we choose Zomato as a benchmark because it is professionally designed for restaurants and controlled by a centre. Zomato company directly works with restaurants' owners and consumers to verify all information before it is published [6] compare its accuracy with results obtained by TrustBF.

Table 1 demonstrates the proximities of each restaurant with three kinds of foods which are a bakery, rice, or noodles. The expertise of agents is referred from their historical comments and the content of these comments. The result of review rates and accuracy in three applications is shown in Table 2. It also shows that the accuracy of TrustBF 0.947 is quite higher than Google 0.88.

5.2 Comparision of Collective Intelligence Factor between TrustBF and Backfeed

In this experiment, we run 200 replications with 10 services per replication for two cases, one for Backfeed and one for TrustBF. We assume each service requires 20 agents to evaluate. Reputation payment skewness γ is 0,01. Adjustable parameters d= 0.01, s= 0.1, and q= 0.02.

Experimental scenarios

Scenario 1: Running with Backfeed protocol to find the accuracy and reputation reward of evaluators in 200 replications. The expert-trust is ignored because Backfeed does not involve this parameter in the system.

Scenario 2: Running with TrustBF protocol. The expert-trust will be set randomly from 0.5 to 1 all services.

The results of Collective Intelligence factor analysis are in Figure 3. It is clear that TrustBF obtains a better CI_f with an earlier convergent point about after 40 replications. In Backfeed experiment, CI_f converges after 100 replications. The variance of CI_f data set in Backfeed is much more than in TrustBF. Therefore, TrustBF is more reasonable reputation protocol which can provide a reliable CI_f.

6 CONCLUSION

In conclusion, this research generally defined the problem of trustworthiness of freely shared information on crowd environments such as social media, where consumers have different expertise and backgrounds. We combined the advantages of content-driven and user-driven trust models and use the crowdsourcing process and blockchain-based consensus theory to propose a new protocol named TrustBF. In this model, we defined a weighted consensus mechanism according to expert-based trust and arrival time of evaluators to calculate the content-trust of shared information. Furthermore, accuracy and collective intelligence factor are defined to assess the effectiveness of our model and compare it with existing approaches. Experimental results showed that the accuracy of the proposed approach is much higher and our approach has a better positive CI_f value than existing applications.

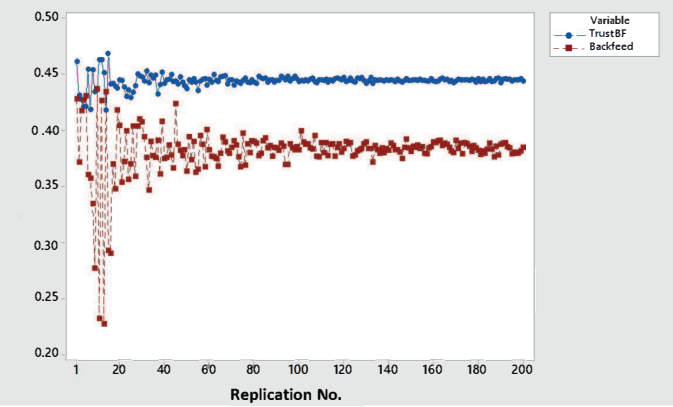


Figure 3: Convergence of CI_f in Backfeed and TrustBF

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Table 1: Proximities of different services.

Name of Restaurant	Bakery	Rice	Noodle
Guerilla Espresso Bar	0.9	0	0.1
Bite Cafe	0.5	0	0.5
Burger King Queen St	1	0	0
BBQ Duck Cafe Queen St	0	0.3	0.7
Lim Thai	0.1	0.4	0.4
Kebab Queen St	0.3	0.7	0
Sushi Pac	0.1	0.9	0
The Kimchi Project	0.3	0.4	0.4
MacDonald's Queen St	1	0	0
Saigon Kitchen	0.1	0.5	0.4

Table 2: Comparison of different approaches with Zomato.

Name of Restaurant	Zomato RR	Google RR	TrustBF RR	Google ACC	TrustBF ACC
Guerilla Espresso Bar	0	5	0	0	1
Bite Cafe	3.5	3.7	3.6	0.94	0.97
Burger King Queen St	2.9	3.6	3.0	0.76	0.96
BBQ Duck Cafe Queen St	4.0	4.1	3.8	0.98	0.95
Lim Thai	3.9	3.5	3.7	0.90	0.95
Kebab Queen St	2.9	3.6	3.4	0.76	0.83
Sushi Pac	4.2	4.0	3.9	0.95	0.93
The Kimchi Project	4.5	4.4	4.6	0.98	0.98
MacDonald's Queen St	2.8	3.6	3.0	0.71	0.92
Saigon Kitchen	4.1	4.3	4.0	0.95	0.98
Mean of Accuracy				**0.88**	**0.947**

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