

# A Blockchain-Enabled Quantitative Approach to Trust and Reputation Management with Sparse Evidence

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## Abstract

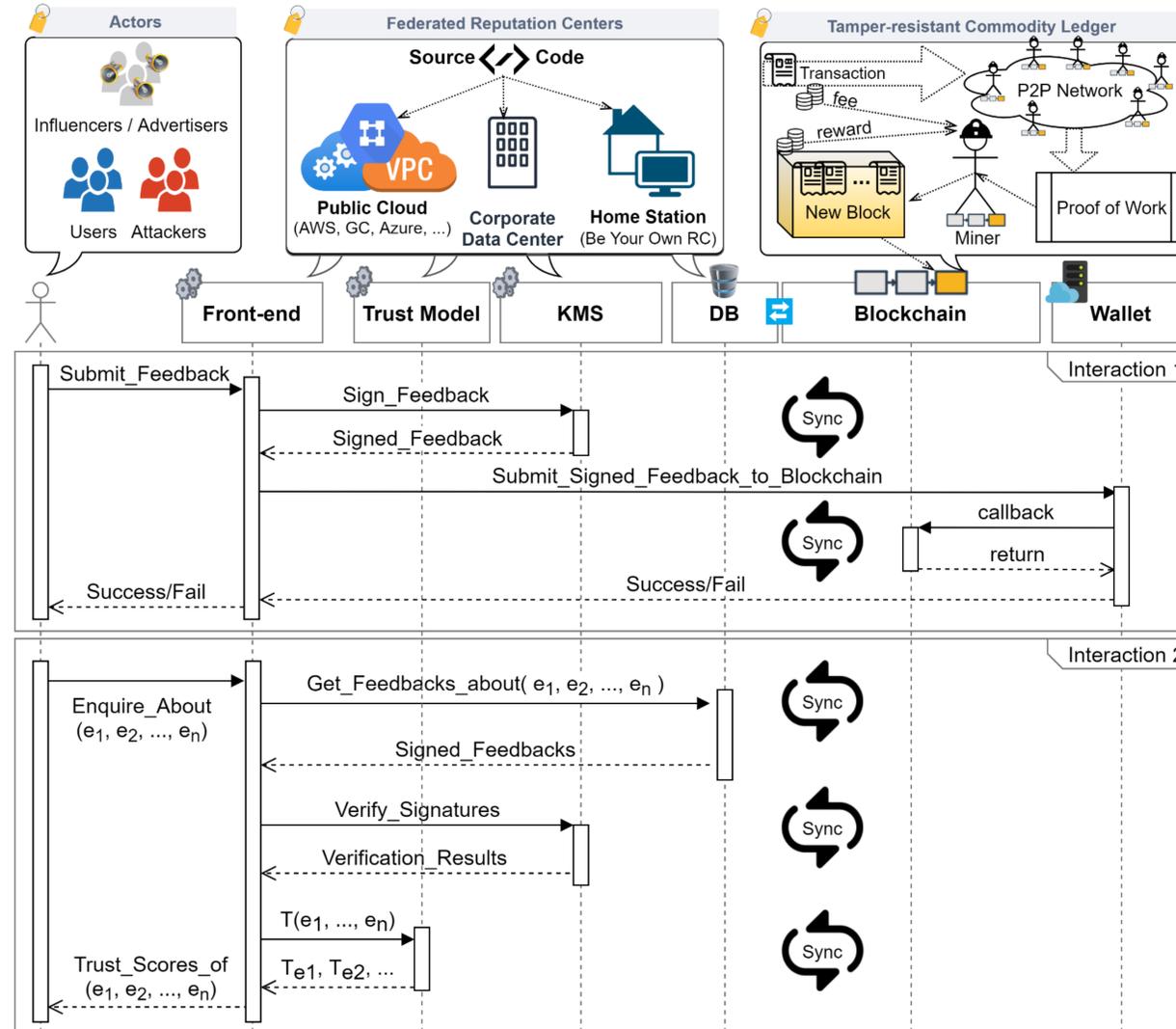
The prevalence of e-commerce poses new trust challenges that render the traditional Trust and Reputation Management (TRM) approaches inadequate. The first challenge is that TRM is built on evidence but evidence is becoming increasingly sparse because nowadays users have many more venues to share information. This makes it hard to derive trust models that are robust to attacks such as whitewashing and Sybil attacks. Second, the cost of attacks has reduced significantly due to the widespread presence of bots in e-commerce applications, which tends to invalidate the traditional assumption that majority users are honest. In this paper, we propose a new TRM framework called BEQA, which uses Blockchain to transform multiple disjoint and sparse sets of evidence into a single and dense evidence set. To address the second challenge, we introduce and formulate the cost of Sybil attacks using Blockchain transaction fees. In addition, we make a key observation that existing trust models have overlooked publicity (evidence originating from influencers) that exist in e-commerce applications. Thus, we formulate publicity as a whitewashing deposit such that a higher level of publicity will impose higher cost on Sybil attacks.

## Design of BEQA

**Feedback.** We use the term feedback to refer to the information shared by a user about an entity. A feedback  $i$  contains a score which we denote by  $v_i$ .

**Blockchain transaction fee.** The Blockchain is a tamper-resistant record-keeping commodity, which means the records are tamper-resistant regardless of who keep them. This, has been time-tested the longest in Bitcoin [3,4,5] for 12 years. Adding records will incur a *transaction fee* to be paid to the record-keepers who are referred to as *Miner*.

We illustrate the process overview of BEQA in Fig. 1. As illustrated in interaction 1, to submit a feedback about an entity  $e$ , a user first signs the feedback with its own private identity key. Thus, each user has a randomly generated key pair (not that of the Blockchain), which makes BEQA robust against *repudiation attacks*. Next, the user submits the signed feedback to Blockchain using a wallet (which is a software used in Blockchain to perform transactions). This will incur the user a transaction fee  $f_i$ ; when the transaction is confirmed on Blockchain, the feedback is assigned a time-stamp  $t_i$ . As illustrated in interaction 2 (lower part of Fig. 1), when a user enquires about the trustworthiness of some entities  $e_1, e_2, \dots, e_n$ , BEQA fetches from a database all the existing feedbacks for those entities as well as the corresponding fees and timestamps. This database is synchronized with the Blockchain (only on transactions relevant to the BEQA framework). Examples of database technologies, which can perform targeted crawling and indexing of the Blockchain, can be found in [1,2].



**Figure 1:** Sequence diagram of the processes in BEQA. Interaction 1 illustrates the assessment data submission process. Interaction 2 illustrates trustworthiness enquiry process.

This also allows us to have federated reputation centers who can not cheat but can prune the feedbacks in compliance with local regulations and applicable laws.

Next, BEQA verifies the user signatures of these fetched feedbacks. This prevents identity attacks in which an attacker associates its malicious feedback with a legitimate user's identity. Finally, BEQA's trust model, which is explained in the next section, uses Blockchain transaction fees to quantify the cost of whitewashing and Sybil attacks and provide a robust assessment of the trustworthiness of entities  $e_1, e_2, \dots, e_n$ .

## Trust Model

BEQA assigns a weight of zero to feedbacks from publicity influencers, and hence filters out their opinions; but BEQA uses their total spend on transaction fees as a whitewashing deposit. BEQA weights the remaining of the feedbacks proportionately to the transaction costs incurred by the submitter. This costs are grown over time using an exponential growth function with an unknown growth rate. This way, BEQA quantifies the weight of a feedback as a function of this growth rate.

Formally, let  $f_j$  be the transaction fee of feedback  $j$ ,  $A_e$  be the set of all feedbacks about entity  $e$ , and  $B_i$  be the set of all feedbacks submitted not later than feedback  $i$  by the submitter of  $i$  about all entities including but not limited to  $e$ .

We obtain the publicity of an arbitrary entity  $e$  from (1) where  $\mu_x, \sigma_x^2, S_x$ , and  $K_x$  are the first four statistical moments of the set  $\{x_i = \sum_{j \in B_i} f_j \mid i \in A_e\}$  as follows:

$$P_e = \left\{ i \in A_e \mid x_i \geq \mu_x + \sigma_x \left(1 - \frac{1}{K_x}\right) \left(\frac{2}{\pi} \tan^{-1}(-|S_x|) + 3\right) \right\} \quad (1)$$

We define the weight of a feedback  $i$  about an entity  $e$  as  $w_i$ :

$$w_i = \begin{cases} \sum_{j \in B_i} f_j (1 + r_e)^{t_i - t_j} & i \notin P_e \\ 0 & i \in P_e \end{cases} \quad (2)$$

where  $t_i$  and  $t_j$  are the timestamps of feedback  $i$  and feedback  $j$  respectively,  $P_e$  is the set containing the publicity of entity  $e$ , and  $r_e$  in (2) is a growth rate that we calculate for each entity dynamically using (3) and (4), given a set of entities  $E$ .

$$R_0^{max} = \min \left\{ \arg \max_{r_e} \left( \sum_{i \in A_e} w_i < \sum_{i \in P_e} \sum_{j \in B_i} f_j \right) \mid e \in E \right\} \quad (3)$$

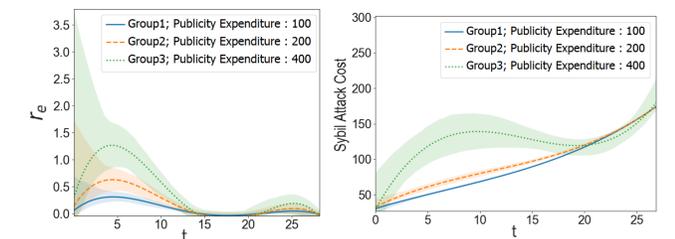
$$r_e = \frac{\sum_{i \in P_e} \sum_{j \in B_i} f_j}{\max \left\{ \sum_{i \in P_{e'}}, \sum_{j \in B_i} f_j \mid e' \in E \right\}} \times R_0^{max} \quad (4)$$

Having obtained  $r_e$  for  $e \in E$  from (4), we can compute the trustworthiness of each entity using (5).

$$T_e = \sum_{i \in A_e} v_i \cdot w_i / \sum_{i \in A_e} w_i \quad (5)$$

## Evaluation

We simulate a TRM scenario with three groups of entities. The only difference between the groups is their publicity expenditure which we define as the total spend of their publicity influencers. That is, the number of the total transactions of the influencers of an entity is a random variable with a mixture of uniform distributions with different means of 100, 200, and 400 and equal mixture weights. At each time-step of the simulation, each entity interacts with 3 percent of randomly chosen honest users. Then, these users each submits a feedback which incurs the user a transaction fee that we treat as the cost unit. We say a Sybil attack is successful if the feedbacks of the attacker about the target entity outweigh that of the honest users. The results show that in general a higher publicity expenditure leads to a higher Sybil attack cost which is a desired property.



**Figure 2:** Simulation results:  $r_e$  and Cost of a successful Sybil attack for entities with different whitewashing deposits at each time step.

## References

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