Credibility Model based on Space-Time Information and Interactive Evaluation in sharing model

Xiaobin Zhang *, Jiacheng Zhang
School of Computer Science, Xi’an Polytechnic University, Xi’an, 710048, China.
*834550537@qq.com

Abstract. Existing reputation calculations are mostly based on malicious behavior and other comments. They fail to effectively integrate impacting factors, ignoring the authenticity of evaluation and the complexity of interaction. A user reputation model based on spatio-temporal information and interactive evaluation is presented: user reputation is affected by ontology and evaluation reputation, and they interact with each other. Considering the synthetical influence of time, space and behavior, a time-space-behavior three-layer model is constructed to measure the time-space impact on ontology and the behavior impact on evaluation reputation; distributing weight to ontology and evaluation reputation, the reputation formula is established to obtain the user reputation. Experiments show the reputation model considers the influence of time, space and behavior on the ontology and evaluation reputation. The higher accuracy of the calculated user reputation has a higher application prospect for sharing mode user reputation evaluation.

1. Introduction
In recent years, with the development of sharing economy and mobile sensing, many smartphone-based participatory sensing systems have been valued and applied [1], such as data perception [2], disaster prediction [3], flood prevention [4], forest protection [5], etc.

User reputation as a key factor to determine the quality of information and service in participative perception has been widely valued [6]. Traditional reputation calculation principally aims at users by identifying malicious operations and other evaluations. It lacks comprehensive analysis of affecting factors, and is difficult to satisfy the authenticity and reliability of transactions under the sharing economy. A series of research on user reputation model has been carried out in academia. [7] considering consumer feedback credibility and collusion factors, a reputation model MASPRep is proposed to help consumers find honest providers;[8]a trust model METrust with consistency factor of mutual evaluation and time decay function is proposed to suppress the dishonest evaluation;[9]a new credibility visualization method is presented by filtering evaluation information ,fusing main evaluation and standardizing entity reputation;[10] a credibility verification mechanism based on hash tree is proposed by extending cloud users' trust base to virtual machines, which solve the trust problem of virtual machines relied on in cloud computing;[11] considering the multi-dimension of trust model, the non-uniform estimator representing individual , total sample mean and the weighted sum of collective mean and the uniform Bühlmann confidence estimation are obtained by projection;[12] a trust management scheme based on time window and BETA distribution is proposed by introducing control factor Fc to prevent time varying estimation;[13] a pre-reputation management model based on EigenTrust is proposed by using personalized pre-trust and its transitivity to ensure the trust spread only within trusting circle;[14] an iterative reputation ranking method with high performance in accuracy and robustness is proposed by introducing reputation redistribution to enhance the impact of high-reputation users and penalty factor to
resist malicious behavior. The above proposed different trust models to study credibility verification, reputation evaluation, estimation and communication. However, the authenticity and complexity of users and the interaction are not taken into account, and the influence factors such as time, space and so on are not taken into.

In the sharing mode, the trust mechanism ensuring the normal interaction between users has been emphasized and popularized. In this paper, a reputation computing model based on spatio-temporal information and interactive evaluation is proposed. The model divides user reputation into ontology reputation based on user attributes and evaluation reputation based on interactive behavior. Ontology reputation mainly refers to the basic attributes of users (such as personal information integrity and behavior reliability, etc.), evaluation reputation mainly refers to the interactive evaluation when users actively share and interact. By constructing a three-layer time-space-behavior model to measure the influence of time-space on ontology reputation and the influence of user behavior (interactive evaluation) on evaluation reputation. The real evaluation is selected to introduce the behavioral credibility, the spatio-temporal behavioral weight is defined to construct the ontology reputation and the evaluation reputation function.

2. Credibility Model based on Space-Time Information and Interactive Evaluation

2.1. The time-space-behavior three-layer model
Considering the influence of time, space, and behavior on user reputation, a three-tier model of time-space-behavior is constructed. To measure the impact of time and space on ontology reputation time weight is defined by introducing time credibility and reasonable time, space weight is defined by introducing reasonable region deviation and behavior diversity; spatio-temporal-behavioral weight is defined by introducing reasonable evaluation and behavioral credibility to measure the impact of behavior on evaluation reputation under certain spatio-temporal factors.

Assuming that $E = (t, s, B)$ is a three-level model of time-space-behavior(Fig.1), behavior factor $B(u) = \{U_i, U_j, U_i \rightarrow U_j\}$. The behavior of N users in ti si forms a reasonable area $B_{t-s}$, the jth user deviating from the reasonable area is $P_{t-s}$, the reputation function of user j can be expressed as $f_j: \{t, s, P_{t-s}\} \rightarrow Cre_j$.

![Fig. 1 Time-Space-Behavior Three-Layer Model](image_url)

2.2. Time-space factors and ontology reputation
Ontology reputation mainly depends on the integrity of user identity, the reliability of behavior and other related factors. When the user interacts at the first time, the ontology reputation is only determined by the registration information; with the increasing of interactions, the reliability of behavior affects the ontology reputation. To measure the reliability of behavior and calculate the ontology reputation, temporal and spatial factors are introduced.

1. Time Factor
The valid time spent by N users in completing behavior B at S-point is defined as reasonable time under certain location-behavior. There is a deviation $\theta_t$ between the actual time $t_{ea}$ and the estimated time $t_{est}$. $\theta_t$ determines the credibility of the actual time $Cre_t$. The reasonable time is $Rea_t$. The calculation formula as follows:
\[\theta_t = \sum_{i=1}^{n} (trea_i - test_i) \quad (1)\]

\[(Cre_t)_i = \left(\frac{trea_i}{\theta_t}\right) \times 100\% \quad (2)\]

\[Rea_t = \frac{1}{n} \sum_{i=1}^{n} (Cre_i \times (trea_i - \overline{trea}) \quad (3)\]

To measure the time impact on the ontology reputation, the time weight \( W(t) \) is calculated by exponential function \([15]\):

\[W(t) = \frac{e^{\text{Cre}(t)}}{\sum_{t \in T} e^{\text{Cre}(t)}} \times |t - \text{Rea}| \quad (4)\]

3. Spatial Factors

Reasonable behavior area is introduced to measure the impact of spatial on ontology reputation under certain time-behavior. Reasonable behavior area is related to the access area and the diversity of behavior, obtained by computing the information entropy \([16]\).

Establishing warp-latitude (x-y) coordinate in the s layer, transforming space points into rectangular and eliminating unreliable points to obtain the reliable area \( S_r \). The total number of behavior points for all users in \( S_r \) is defined as \( SP_r \), for the per user in \( S_r \) is defined as \( SP_i \) and in the space layer as \( SP_m \), and the number of users per action point as \( M (j = 1,2,3,...,m) \). The diversity and the rationality of each behavior point are defined as \( \text{Div}_i \) and \( \text{Rea}_n \). The calculation formula is as follows:

\[\text{Div}_i = \frac{SP_i}{SP_n} \times \log_2 \left(\frac{SP_i}{SP_n}\right) \quad (5)\]

\[\text{Rea}_n = \text{Div}_i \times \frac{M_j}{SP_r} \quad (6)\]

(5) (6) remove the low rationality behavior points to obtain a reasonable behavior area \( \text{Rea}_n \), to measure the spatial elements impact on the ontology reputation the space weight \( W(s) \) is defined:

\[W(s) = \frac{\sum_{s \in S \cap \text{Rea}(s)}}{\sum_{s \in S} ||P_t||} \times ||P_t|| \quad (7)\]

When the space layer is transformed into the coordinate system, the linear distance between user behavior points and reliable area \( ||P_t|| \) and between user action points and coordinate circles \( ||s|| \) can be obtained.

By constructing a time-space-behavior three-tier model, the weight of time and space on ontology reputation is extracted and the ontology reputation function is constructed:

\[\text{Eva}(u) = \sum_{i=1}^{m} (W(t) \times \text{Cre}_i + W(s) \times \text{Rea}_n) \quad (8)\]

\( m \) represents the number of action points, \( W(t), W(s) \) represent the influence weight of time and space, \( \text{Cre}_i \) and \( \text{Rea}_n \) represent time credibility and spatial rationality.

3.1. Spatiotemporal - behavioral and interactive evaluation

When multiple users interact, different user produce different reputations (-10-10, step is 1), the social circle under behavior b in a certain time-space is extracted to construct the evaluation reputation weighted graph. (User i and j may generate multiple evaluations in the same social circle. The mean of evaluations is the final evaluation.)

When all users in the social circle generate reputation evaluations for core user, the anomaly value is detected by anomaly detection to select real evaluation and calculate evaluation reputation. The anomaly detection method is as follows:

The average \( \text{value} \) and variance \( \sigma_{\text{value}}^2 \) of evaluation are calculated as formulas:

\[\text{value} = \frac{1}{n} \sum_{i=1}^{n} \text{value}_i \quad (9)\]

\[\sigma_{\text{value}}^2 = \frac{1}{n} \sum_{i=1}^{n} (\text{value}_i - \text{value})^2 \quad (10)\]
p(x) can be obtained from the average and variance:

\[ p(x) = \prod_{i=1}^{n} p(x_i; \text{value}_{i}, \sigma_{\text{value}}^2) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi\sigma_i}} \exp \left( -\frac{x_i - \text{value}_i}{2\sigma_i^2} \right) \]  

(11)

Select boundary \( \epsilon \) when \( p(x) < \epsilon \), the evaluation is abnormal; otherwise the evaluation is reasonable.

After obtaining reasonable evaluations, the time-space-behavior weight \( W(b-t, s) \) is defined to measure the impact of behavior on evaluation reputation, which is affected by behavioral credibility \( Con \), and the formula is as follows:

\[ W(b-t, s)_i = \frac{e^{Con(i,b)}}{\sum_{b \in B} e^{Con(i,b)}} \]  

(12)

\[ Con(i,b) = P(t | \text{Rea}_t, \text{Cre}_t)P(s | P_{t-s}, P(Div)) \]  

(13)

\[ P(t | \text{Rea}_t, \text{Cre}_t) \] is the reliability of time based on reasonable time \( \text{Rea}_t \) and credibility time \( \text{Cre}_t \), \( P(s | P_{t-s}, P(Div)) \) is the reliability of space based on the deviation value \( P_{t-s} \) of space point from rational area and the diversity of behavior:

\[ P(t | \text{Rea}_t, \text{Cre}_t) = \text{Cre}_t \times \frac{|t - \text{Rea}_t|}{\text{Rea}_t} \]  

(14)

\[ P(s | P_{t-s}, P(Div)) = \frac{P_{t-s}}{\sqrt{s_x^2 + s_y^2}} \times \frac{\text{Rea}_s}{\text{Div}_s} \]  

(15)

We have stipulated the average of multiple evaluation in the same social circle is the final evaluation, the user evaluation credit \( \text{EvalInfo} \) can be expressed as follows:

\[ \text{EvalInfo}(u) = \sum_{i=1}^{n} (W(b-t, s)_i \times Con(i,b) \times \text{value}_i) \]  

(16)

\( n \) denotes all the reasonable evaluation, \( Con(i,b) \) denotes behavior credibility and \( \text{value}_i \) is the evaluation reputation of i to core user.

4. Credit Calculation

User reputation is calculated by aggregation weighting of ontology and evaluation reputation. When the user first register and has no interactions, the evaluation reputation is 0 and the ontology reputation determines the user reputation. With the increase of interactions, users get evaluations while their own behavior is also affecting the ontology reputation. When the evaluation is less, the evaluation reputation can not fully reflect the user reputation, and the ontology reputation still occupies a large proportion, with the increasing of evaluations, the evaluation reputation is the main part of users’ reputation, the reputation of user \( u \) is defined as \( E(u) \):

\[ E(u) = \text{Eva}(u) \cdot e^{-m/M} + \text{EvalInfo}(u) \cdot (1 - e^{-m/M}) \]  

(17)

\( \text{Eva}(u) \) represents the ontology reputation and \( \text{EvalInfo}(u) \) is the evaluation reputation, \( m \) is the number of interactions and \( M \) is used to control the impact weight of ontology and evaluation reputation. This value can be determined by the average of the reputation converges. The specific algorithm is as follows:

Algorithm1 Reputation Algorithms

| input: U={U_1, U_2, U_3, ..., U_n}, E = (t, s, B), Core User u, B(u)={U_i, U_j, U_i \rightarrow U_j}; |
| output: User reputation E(u); |
| process: |
| 1. for b = 1 \( \rightarrow \) m(m is the number of user actions) |
| Construct the time-space-behavior three-tier model; |
| (1) - (8) calculates the weight of time and space and ontology reputation; |
| (10)-(11) eliminates unreliable evaluations; |
| (12)- (15) calculates behavioral credibility, spatiotemporal-behavioral weights and evaluation reputation. |
| 2. end for |
| 3. (17) calculates user reputation |
5. Experimental Evaluation

This paper uses the Brightkite[17] and Bitcoin Alpha trust weighted signed network dataset[18][19] published by SNAP. The Brightkite, which is derived from a location-based social network service provider and contains 4.5 million public check-in data from April 2008 to October 2010, consisting five fields: user ID, check-in time and location ID, longitude, dimension. Alpha dataset contains 3,783 nodes and 2,416 user interaction edges with weights ranging from -10 to 10 in five different networks. In this paper, we select any interaction information, containing three fields: ID of source user and target user, and the evaluation of source user to the target user. The longitude and latitude are randomly matched with the interactive data to form a test data set containing seven fields: source user ID, target user ID, evaluation mean, initial reputation of source user, Unix timestamp, longitude and latitude.

100 records and core users are chose randomly to measure the influence of time and space on ontology reputation, the result graph is shown in Fig 2.

![Fig. 2 Ontology Reputation Result Graph](image)

Fig 2 a illustrates the impact of time on ontology reputation. The smaller the difference between actual and effective time, the higher the ontology reputation, conversely the lower the reputation. When the difference is maximum, the user only has 1 ontology reputation, and when there is no difference, the user has reputation about 8.4. Fig 2 b illustrates the influence of spatial on ontology reputation. The smaller the difference between longitude and latitude, the closer the user is to the reasonable area the higher the ontology reputation, otherwise the lower the reputation.

By obtaining reliable evaluation and introducing behavioral credibility, the spatiotemporal-behavioral weight is defined to calculate user evaluation reputation, the result shown in Fig 2.
Fig. 3 illustrates the influence of user behavior on evaluation reputation under the joint action of space and time. The higher the credibility of user behavior, the higher the evaluation reputation, conversely, the lower the evaluation reputation. Fig. 3 b illustrates the relationship among ontology, evaluation and user reputation. TargetIdInitialCre, EvaCre and UserValue represent ontology reputation, evaluation reputation, and the user reputation respectively. Figure 3 b shows that user reputation is determined by ontology and evaluation reputation, and the proportion of evaluation reputation increases but the ontology reputation decreases. At last, the proportion of evaluation reputation is about 73% while that of ontology reputation is only about 25%, meanwhile, the highest user reputation is about 5.8 and it is still possible to achieve higher.

Figure 3 c shows the accuracy of using different methods to obtain user reputation. From Figure 3 c, the accuracy of credit judged only by user behavior is about 65%; when time or space factors are introduced, the accuracy rate is higher about 75%; when space-time and behavior factors are considered comprehensively, the accuracy rate is the highest about 83%.

6. Conclusions
This paper proposes a reputation computing model based on spatio-temporal and interactive evaluation. The time-space-behavior three-tier model is established to consider the comprehensive influence of three factors on user ontology and evaluation reputation. Time and space weights are introduced to measure the impact of time-space on ontology reputation. Meanwhile, evaluation credibility and time-space-behavior weights are introduced to measure the impact of user behavior on evaluation reputation.
In summary, this paper introduces the time-space factor to study the comprehensive impact on user ontology reputation under the sharing mode and how to calculate the user evaluation reputation from the interaction evaluation under the limitation of time-space. Later, we will explore how to mine the social circle based on the user's reputation.

Acknowledgments
This work was supported by the Shaanxi Natural Science Foundation(Grant No. 2015JQ5157) and the Graduate Innovation Fund of Xi’an Polytechnic University.

References
[1] Guo B, Yu Z, Zhang D, et al. From Participatory Sensing to Mobile Crowd Sensing[C]// IEEE International Conference on Pervasive Computing & Communications Workshops. IEEE, 2014.
[2] Dong Wang, Amin, M.T., Shen Li, et al. Using humans as sensors: An estimation-theoretic perspective[P]. Information Processing in Sensor Networks, IPSN-14 Proceedings of the 13th International Symposium on, 2014.
[3] Gu S, Govindan R, Aggarwal C, et al. Data Extrapolation in Social Sensing for Disaster Response[C]// IEEE International Conference on Distributed Computing in Sensor Systems. IEEE Computer Society, 2014.
[4] Gisela Wachinger, Patrick Keilholz, and Coral O’Brian. The Difficult Path from Perception to Precautionary Action: Participatory Modeling as a Practical Tool to Overcome the Risk Perception Paradox in Flood Preparedness[J]. International Journal of Disaster Risk Science, 2018, 9(04):472-485.
[5] Pascaline Coulibaly-Lingani, Mulalem Tigabu, Patrice Savadogo, Per-Christer Odén. Participatory forest management in Burkina Faso: Members’ perception of performance[J]. Journal of Forestry Research, 2014, 25(03):637-646.
[6] Yefeng Ruan; Durresi, A. A survey of trust management systems for online social communities—Trust modeling, trust inference and attacks[J]. Knowledge-Based Systems, 2016, Vol.106:150-163.
[7] Zhu W Q. MASPRep: A Reputation Computing Model for Mobile Application Service Providers[C]// International Conference on Information Science & Control Engineering. IEEE, 2016.
[8] METrust: A Mutual Evaluation-based Trust Model for P2P Networks[J]. International Journal of Automation & Computing, 2012, 9(01):63-71.
[9] Yan Z, Jing X, Pedrycz W. Fusing and mining opinions for reputation generation[J]. Information Fusion, 2017, 36:172-184.
[10] Shuaishuai Z, Yiliang H, Xiaoyuan Y, et al. Hash Tree Based Trustworthiness Verification Mechanism in Virtual Environment[J]. China Communications, 2016, 13(3):184-192.
[11] ZHANG Qiang, CUI Qianqian, CHEN Ping. Multidimensional Credibility Estimators with Random Common Effects and Time Effects[J]. Journal of Systems Science & Complexity, 2017, (5):1107-1120.
[12] Weidong FANG, Wuxiong ZHANG, et al. A resilient trust management scheme for defending against reputation time-varying attacks based on BETA distribution[J]. Science China(Information Sciences), 2017, 60(04):60-70.
[13] Li M, Guan Q, Jin X, et al. Personalized pre-trust reputation management in social P2P network[C]// 2016 International Conference on Computing, Networking and Communications (ICNC). IEEE, 2016.
[14] Liao, H (Liao, Hao)1; Zeng et al. Ranking Reputation and Quality in Online Rating Systems[J]. PLOS ONE, 2014, Vol.9(S).
[15] Vahedian F, Burke R, Mobasher B. [ACM Press the 25th Conference - Bratislava, Slovakia (2017.07.09-2017.07.12)] Proceedings of the 25th Conference on User Modeling, Adaptation
and Personalization, - UMAP

[16] Shannon C E. A mathematical theory of communication[J]. Bell Systems Technical Journal, 2014, 27(4):623-656.

[17] E. Cho, S. A. Myers, J. Leskovec. Friendship and Mobility: User Movement in Location-Based Social Networks ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD), 2011.

[18] S. Kumar, F. Spezzano, V.S. Subrahmanian, C. Faloutsos. Edge Weight Prediction in Weighted Signed Networks. IEEE International Conference on Data Mining (ICDM), 2016.

[19] S. Kumar, B. Hooi, D. Makhija, M. Kumar, V.S. Subrahmanian, C. Faloutsos. REV2: Fraudulent User Prediction in Rating Platforms. 11th ACM International Conference on Web Search and Data Mining (WSDM), 2018.