A Novel Equitable Trustworthy Mechanism for Service Recommendation in the Evolving Service Ecosystem

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Abstract. Trustworthy service recommendation has become indispensable for the success of the service ecosystem. However, traditional trustworthy methods somehow overlook the service equality which result into a "rich-get-richer" effect and become a barrier for the novice services to startup and grow. This paper addresses this problem through a novel equitable trustworthy mechanism, which distinguished the difference between the novice and mature services over the trustworthy service recommendation. The results based on the real-world service ecosystem, i.e. ProgrammableWeb, show that our method achieves a better performance in equality guarantee and white-washing prevention. Thus it can promote the service ecosystem's healthy growth in a fair manner.

Keywords: Evolving Service Ecosystem, Equality Trustworthy Recommendation, Equality Guarantee, White-washing Prevention.

1 Introduction and Related Work

With the wide adoption of Service Oriented Architecture (SOA), more and more services are available over the Internet. Many trustworthy recommendation approaches [1-7] have been proposed to help the developers to select the desirable services against many other alternatives. Though these approaches have been successful in addressing this information overload problem to certain extent, most of them somehow overlook the equality and fairness in the evolving service ecosystem. Firstly, the assignment of initial trust value to new services, which is known as the trust bootstrapping issue [8], did not get much attention while it will affect the robustness of the trust model. Additionally, as only the services with high trust value are recommended while the new services may not be able to win a consumer's trust to build the reputation, these traditional trustworthy mechanisms become barrier for the use of new services and result into a "rich-get-richer" effect in the system [5]. Thus how to provide global equality for both existing services and newcomers becomes important for the healthy growth of service ecosystem.

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Equality, also known as fairness, has been studied in many disciplines [9]. For the service ecosystem, we define equality as both existing services and newcomers have a fair chance of being selected and building trust. Some try to offer fairness from the bootstrapping aspect [8,10-12]. However, it is non-trivial to assign an equitable bootstrapping trust value for the new services. Actually, the problem of the unfairness in the traditional trustworthy methods arises from the situation that the new services have to compete with the ones which have built trust over time as soon as they enter the ecosystem. Thus the basic idea here is to split all the services in the same domain into the novice service queue and the mature service queue so that the new services only compete with new ones until they grow matured. Difference mechanisms for the novice and mature services over the four-step trustworthy service recommendation (trust bootstrapping, service organization, recommendation generation and trust updating) need to be designed to distinguish the difference between them. Hence the major contributions of this paper can be summarized as follows:

- The formal definition of equality guarantee in the evolving service ecosystem is presented.
- A four-phase equitable trustworthy recommendation model is proposed to guarantee the global fairness.
- The empirical experiments shows that the proposed approach can achieve a better performance in equality and promote the healthy growth of the ecosystem.

The remainder of this paper is organized as follows. Section 2 describes the formal definition of equality guarantee. Section 3 presents the proposed four-phase equitable trustworthy recommendation model. Section 4 reports the experimental result. Section 5 concludes the paper.

2 Equality Guarantee

Equality measures are based on the proportions of shared resources in the system. In the service ecosystem, services with the similar functionality will compete with each other to gain the opportunity of being selected by consumers. As a consequence, in this paper, the resource in service ecosystem can be defined as *the opportunity of being selected in the composition.*

Equality Metric:
Gini Index has been widely used for fairness measure [13]. Here we reuse Gini Index as service equality metric in a service ecosystem. Suppose S is the set of services in the service ecosystem. According to the number of resources allocated to each service, they can be divided into x subset. Let $S_{r=i}$ present the services with i resource, then our Gini index is defined as:

$$Gini = 1 - \sum_{i=1}^{x} \left(\frac{|S_{r=i}|}{|S|}\right)^2 \tag{1}$$

Here the function $|*|$ refers to the number of item in any given set. Additionally, in a similar manner to how Shannon defines information, the entropy-based fairness [14] in the service ecosystem can be defined as:

$$EnFair = -\sum_{i=1}^{x} \frac{|S_{r=i}|}{|S|}\log\left(\frac{|S_{r=i}|}{|S|}\right) \tag{2}$$

As the traditional trustworthy recommendation approaches may harm usage diversity and become the entry barrier for the new services, here we also considered the recommendation diversity which is defined as follows:

$$ReDi = \frac{|RS|}{|S|} \tag{3}$$

Here RS refers to all the unique services which are recommended to the consumers.

White-washing Prevention:

White-washing phenomenon means that services may re-enroll into the ecosystem as new services to white wash their historical records. Suppose $ARB(s_i)$ refers to the allocated resource number of service s_i if it keeps the same behavior as before, $ARA(s_i)$ refers to the one after it white-washes its historical information. Thus we can define the white-washing prevention effect for this service as follows:

$$WWP(s_i) = \frac{ARB(s_i)}{ARA(s_i)} \tag{4}$$

Then the white-washing prevention effect for the service ecosystem can be considered as the average of the white-washing prevention effect for each service:

$$WWP = \frac{1}{|S|}\sum_{s_i \in S} \frac{ARB(s_i)}{ARA(s_i)} \tag{5}$$

If $WWP > 1$, the system can prevent the white-washing phenomenon. A larger WWP indicates a better performance in white-washing prevention.

3 Equitable Trustworthy Recommendation Mechanism

In the evolving service ecosystem, new services are published into the ecosystem over time and the initial trust value is assigned to each service. Then the services with similar functionality are organized into the same service domain. In order to fulfill the composition requirements raised by the consumers, the requirements will be decomposed into different domains and mapped to the related service domain. The candidates will be selected from the domain and presented to the consumers. Finally, each service will build its trust based on its usage and feedback. Hence the trustworthy service recommendation consists of the following four important steps: trust bootstrapping, service organization, recommendation generation and trust updating. Notes that the requirement decomposed and domain mapping are not included as they are dealt in the same way for both novice and mature services. Hence our equitable trustworthy recommendation mechanism (ETRM) works in four steps as follows:

Trust Bootstrapping (TB):
The goal for the trust bootstrapping phase is to assign an initial trust value T_{ini} to the new services. This paper considers the following strategies:

*Default-based Bootstrapping (DB)***:**
The default-based bootstrapping strategy assigns a default trust value to the new service [12]. The default value can vary between 0 and 1. If a low initial value is given, this strategy turns out to be the punishing approach [11].

Adaptive Bootstrapping (AB):
The adaptive bootstrapping approach calculates the initial trust value based on the rate of maliciousness in the system [8]. Instead of using the maliciousness rate, we straightforwardly assign the new services with the average trust value in the system.

Service Organization (SO):
The services in each domain are organized into the novice and mature service queues. Some novices are expected to build enough reputation and grow into matured. Hence, we need to consider the migration rule to move a novice services into mature:

Migration Principle. Given the trust threshold T_{mature} and the protection time-window A_{mature}, for the novice service ns, if $T(ns) \geq T_{mature} \,||\, A(ns) \geq A_{mature}$, then migrate ns into the mature queue.

Here $T(ns)$ refers to the service's trust, $A(ns)$ refers to the service's age in the ecosystem which means the time since it is enrolled into the system.

If the trust threshold is set lower than the initial trust value $T_{mature} < T_{ini}$ or the protection-time-window is set as $A_{mature} = 0$, then the organization strategy become the same as the traditional trustworthy approaches. Hence, the traditional service organization strategy can be considered as a special case in our proposed model.

Recommendation Generation (RG):
For each requirement of a consumer for a particular functionality in a service domain, the goal for a recommendation system is to generate *k* service candidates from the service domain and then presented to the consumer. This task includes two steps:

Candidate Picking (CP):
In this step, *q* services with top *q* trust value in the mature services queue and the other *k-q* services with top *k-q* trust value in the novice services queue are selected to

generate the recommendation list. Obviously, the proportion of the mature services in the recommendation candidates is adjustable to reflect an ecosystem's principal and business model. For example, if the system is conservative, q can be very big (even $q = k$, *where being equivalent to no* novice services queue). If the system welcomes and encourages new services, a smaller q would be selected, e.g., $q = k/2$.

Recommendation Presentation (RP):
Based on whether the q mature service candidates and the k-q novice service candidates are merged together, two different presentation strategies (*ps*) to present the recommendation list to the consumers can be offered:

- *Single List Presentation Strategy (SLP):* The mature service candidates and the novice service candidates are merged into a single list. Thus it is "One Domain One Recommend List".
- *Double List Presentation Strategy (DLP):* The mature service candidates and the novice service candidates are recommended to the consumer separately using two lists for consumers to select. Thus it is "One Domain Double Recommend List".

Trust Updating (TU):
The service's trust is constructed based on its usage. Also as it has temporal sensitivity and the older perceptions gradually fade, it will evaporate over time. Hence, the trust updating contains two operations:

Feedback Update (FU):
If a service is selected, it will receive a feedback rating from its consumers. Many approaches have been proposed to calculate this feedback trust based on the user ratings. Here we use a simple approach from our previous work. Suppose that in time interval t, the feedback trust for a service s_i from its jth composition $c_{t,j}$ is $CT_{t,j}(s_i)$, then its trust after $c_{t,j}$ occurs is:

$$T_{t,j}(s_i) = (1-w)T_{t,j-1}(s_i) + w \times CT_{t,j}(s_i) \tag{6}$$

where $w = [0,1]$ refers to the weight of the feedback trust which varies from 0 to 1.

Evaporation Update (EU):
The empirical study shows that the service's trust is temporal sensitivity and will evaporation over time [5]. Similar to our previous work [4], the evaporation factor can be obtained via the following equation:

$$T_t(s_i) = T_{t-1}(s_i) \times e^{-\lambda} \tag{7}$$

where $T_t(s_i)$ refers to the service's trust at the end of time interval t and λ is the parameter to control the evaporation speed. Obviously, we can use different λ for mature and novice services so that the trust values will evaporate in a different speed.

Hence we note λ_m as the evaporation speed control parameter for mature services and λ_n for novice services.

4 Experiments Based on ProgrammableWeb

To examine the performance of the proposed approach and make the simulation experiment fitting with the actual data, the same to our previous work [4], we obtain the data set from ProgrammableWeb, by far one of the largest online service ecosystem, which contains 7077 services and 6726 compositions over 86 time intervals. Each service contains the information such as name, domain and publication date. Each composition contains the information such as name, creation date, the invoking services' domain list and its visited number as well as the user rating which are used to calculate the composition's feedback trust for the invoking services.

As discussed before, by setting the protection-time-window as 0, the proposed ETRM will reduce to the traditional trustworthy model. The recommendation candidates will all be mature and the presentation strategy will only be *SLP*. Also, only one evaporation speed control parameter will be considered. Thus, we can get the traditional trustworthy models by setting $A_{mature} = 0$, $q = k$, $ps = SLP$, $\lambda_m = \lambda_n$. Hence based on the different bootstrapping strategies, we consider the following baselines:

- Tradition Trustworthy with Default Initial Trust

The bootstrapping strategy is set as *DB* and the initial value T_{ini} is given. If a high initial value is used, $T_{ini} = 0.7$, we get the *None Approach* [12], named as *nTTDIT*; If a low initial value is used $T_{ini} = 0.3$, we get the *Punishing Approach* [11], named as *pTTDIT*.

- Tradition Trustworthy with Adaptive Initial Trust

The bootstrapping strategy is set as *AB* and the average trust value in the community is used as the initial trust value. We get the *Adaptive Approach* [8], named as *TTAA* in this paper.

Result and Discussion

Equitable Guarantee

First of all, we consider the three ETMs which have different parameter combinations. Here, for *nETMDIT* and *pETMDIT*, we set the $T_{mature} = T_{ini} + 0.2$ so that the novice services can move to the mature queue after they build their trust. For the *ETMAA* with the adaptive initial strategy, we just use the average trust value over time as the threshold, which is 0.7 in our experiment. Then we set $A_{mature} = 15$ to make sure the length of the mature and novice queue in the system is comparable. The evaporation speed for both mature and novice services are set as 0.005.

White-washing-prevention
In order to simulate the white-washing prevention phenomenon, given a time interval t_w , all the mature services in the ecosystem are republished. Each service's status is set as novice and the initial trust value are assigned to these services. Then, the total selected frequency of these services after white-washing is collected and the WWP can be calculated. Here, we set t_w as the time interval when the number of the published compositions is half of the total number over the whole period. In order to remove the random effect, we run 5 round simulations for each models and the average WWP is used.

Table 1. Equitable Guarantee Performance Comparision

	None		*Punishing*		*Adaptive*	
	nTTDIT	***nETMDIT***	***pTTDIT***	***pETMDIT***	***TTAA***	***ETMAA***
Gini	0.8394	0.5785	0.8453	0.5883	0.8429	0.6801
EnFair	0.6724	0.8755	0.6687	0.9057	0.6706	0.8088
ReDi	0.1573	0.5335	0.1573	0.4965	0.1573	0.5184
WWP	1.1407	1.3355	1.1439	1.4069	1.1523	1.2124

From Table. 1, we can conclude that the three ETRMs gain better performance than the traditional trust methods. They achieve a 19.31%~31.08% reduction in Gini index, 20.61%~30.21% increases in entropy-based fairness and 215.64%~ 239.16% diversity improvements. This is because of the separation between novice and mature services that makes the novice services gain an equitable opportunity to be recommended and selected by the consumers for the compositions. Also all the three ETRMs gain a 5.22%~22.99% higher WWP than the traditional methods. It means that the white-washing services in our ETRMs g a lower possibility to be reused.

5 Conclusion

The trustworthy service recommendation has become indispensable for the success of a service ecosystem. However, traditional approaches overlook the service equality for the usage of services, which harms the extension and growth of the service ecosystem. To our best knowledge, this is the first work to: (a) identify the service equality problem in the service ecosystem as well as the evaluation metrics including the equality measurement and the white-washing-prevention effect; (b) propose an equitable trustworthy mechanism which distinguishes the difference between mature and novice services to ensure the equality. The empirical experiments based on ProgrammableWeb show the effectiveness and usefulness of the proposed approach for equality guarantee and white-washing-prevention.

In the future, we will further work on the affection of the parameter combinations to the performance and then construct the mathematical model for the equitable trustworthy model as well as the approach to optimize the evolution of service ecosystems.

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