A Recommender System Model Combining Trust with Topic Maps

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Abstract. Recommender Systems (RS) aim to suggest users with items that they might like based on users' opinion on items. In practice, information about the users' opinion on items is usually sparse compared to the vast information about users and items. Therefore it is hard to analyze and justify users' favorites, particularly those of cold start users. In this paper, we propose a trust model based on the user trust network, which is composed of the trust relationships among users. We also introduce the widely used conceptual model Topic Map, with which we try to classify items into topics for Recommender analysis. We novelly combine trust relations among users with Topic Maps to resolve the sparsity problem and cold start problem. The evaluation shows our model and method can achieve a good recommendation effect.

Keywords: Recommender Systems, Trust Model, Reputation, Trust Propagation, Topic Maps.

1 Introduction

With rapid development of Internet, more and more people use online systems to buy products and services (hereafter called items). However, with overwhelming amount of information about items available on the Internet, it is extremely difficult for users to easily find and determine what they would like to buy. Recommender systems aim to recommend the target users with the items which are considered to have high possibilities of meeting their preferences.

Given a huge number of users making commercial transactions online and an even larger amount of items available for sale online, recommender systems have to face two major challenges: **data sparsity** – the average number of ratings given by users is often very small compared to the huge number of items, and **cold start** – the "dumb" users who review few items and provide little information. It causes the problem that a recommender system cannot decide what should be recommended to the target users since it can only directly access to the users' opinions on a small proportion of items. Therefore, the data sparsity is now taken into account by many recommendation methods [9]. The cold start problem is a challenge to recommender systems due to its lack of sufficient information to justify their interests. The traditional solutions to the

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problems are to use a combination of content-based matching and collaborative filtering [21]. Recently, researchers have considered using trust to deal with them [10, 14].

Trust is an assumed reliance on some person or thing, namely, a confident dependence on the characteristics, ability, strength or truth of someone or something [12]. As pointed by Massa [15], recommender systems that make use of trust information are the most effective in term of accuracy while preserving a good coverage. In a trust-based recommender system, trust propagation is computed based on the trust network to derive indirect trust relationships between users, such as in the case of FOAF (friend of a friend) [7] – the framework for representing information about people and their social connections.

In general, the key concepts considered in modeling recommender systems include users, items, and the characteristics of them. Trust-based methods take only users' social links (Trust) into account but ignore the relations among items, which are helpful in predicting users' interest. In order to achieve a good recommendation method, we will combine trust relations among users with similarity relations among items derived by topic maps in an integrated model of recommender systems. This model maintains three types of relationships. The first type is the **trust** relationships among users. The second is the **rating scores** given to items by users, expressing how much users like items. The third one is called **relatedness** of an item to a topic, representing how much the item belongs to this topic, which leads to the computation of similarity relations among items. We use Topic Maps to represent the third type of relationships. Topic Maps is defined as an abstract model for semantically structured, self-describing link networks laid over a pool of addressable information objects [13]. A topic map includes three key components: topics, associations, and occurrences [22]. Using these elements, topic maps can be built in many domains.

The rest of this paper is organized as follows. We introduce the related work in recommender systems, trust and Topic Maps in Section 2. Then in Section 3 we propose our model based on trust and Topic Maps, and we novelly propose a method to propagate trust to determine users' interests and to apply Topic Maps to consider the relationship between items. Then we introduce our datasets for experiments and analyze the experiment results in Section 4. We conclude this paper and point out our future research in the last Section.

2 Related Work

Many efforts have been put in studying and developing recommender systems, aiming to support users doing business online. The major ones include content-based methods, collaborative filtering (CF) methods, hybrid methods - a combination of content-based methods, collaborative filtering methods and others. Recently, researchers are developing methods using trust to analyze users or items thereby to recommend users with items they might like.

The content-based methods analyze the items that are rated by users and use the contents of items to infer users' profiles, which is used in recommending items of interest to these users [2]. More specifically, the TF-IDF (term frequency–inverse document frequency) method, a computation method reflecting how important a word is to a document in a collection, is used to compute similarities of contents [20]. In this method, if two users collect more items with the similar content, they would be more likely to prefer the same items. These methods have been extended to consideration of using the attributes of items (for similarity computation) and the ratings given to items by users (for users profile computation) in construction of recommendations [23]. However, the content-based methods suffer from some shortcomings. Such kind of methods usually needs to collect user profiles. This is a problem of privacy. What is more, the content-based methods may cause overspecialized recommendations that only include items very similar to those of which the user already knows [3].

The CF method uses a database about users' preferences to predict more items users might like [4]. Papagelis et al. [19] propose a recommendation method based on incremental collaborative filtering of users' similarities. This method expresses the new similarity values between two users in relation to the old similarity values, so as to maintain an incremental update of their associated similarity. Zhang et al. [26] propose a recommendation algorithm based on an integrated diffusion method making use of both the user-item relations and the collaborative tagging information. They use a so called user-item-tag tripartite graph as the base of the diffusion process to generate recommendations. This method uses both the user-item relations and the collaborative tagging information to improve the algorithmic performance. The shortcoming of CF methods is that they do not explicitly incorporate feature information and face the sparsity problem and cold-start problem.

The authors of [18] propose a method using a weighted combination to fusion ratings obtained by content-based methods and CF-based methods separately. The weights are adjusted based on the strength of both the content-based method and the CF-based method. As the number of users and ratings given by them increase, the CF-based method is usually weighted more heavily, to take advantage of the wisdom of crowd via globally computing all the ratings. Melville et al. [17] propose an approach using a content-based predictor to enhance existing user data thereby to provide personalized suggestions through collaborative filtering. The content-based predictor accepts the item with a high rating score and rejects the item with a low rating score. However, these methods ignore the important social information which can reflect users' interest.

Trust among users and reputation of users are becoming important and elementary issues in social networking study. As pointed out by Guha and Kumar et al. [8], a user trust network is a fundamental buildings block in many of today's most successful e-commerce and recommendation systems. The authors propose a framework of trust propagation schemes, which appears to be the first to incorporate distrust in a computational trust propagation setting. This paper shows that a small amount of expressed trust or distrust information can be used to predict trust between any two people in the system with high accuracy. Ziegler and Lausen [27] introduce a classification scheme for trust metrics. They present some model constituents for semantic web trust infrastructure in the case FOAF (friend of a friend). However this paper has a limitation that it assumes all trust information is publicly accessible, which, in practice, is nearly impossible. Vydiswaran et al. [25] propose a trust propagation framework to compute how freetext claims of internet and their sources can be trusted by using an iterative algorithm to compute the scores of trust propagation. But this work utilizes a weak supervision at the evidence level, which makes it difficult to be used in other domains. Apart from trust, reputation - a global aggregation of the local trust scores by all the users [11] - is also important because it represents users' trustworthiness from a systemic perspective. Kamvar et al. [11] describe an algorithm to decrease the number of downloads of inauthentic files in a peer-to-peer file-sharing network. This paper assigns each peer a unique global trust value, based on the peer's history of uploads. Adler et al. [1] propose a content-driven reputation system for Wikipedia authors, which can be used to flag new contributions from low-reputation authors, or to allow only high-reputation authors to edit critical pages. Trust-based methods use trust relationships among users to build a social network to link users and use it to derive users' interest. But these methods have a shortcoming that they fail to analyze the relationships among items.

It is important for recommendation to take into account the relationships of items. We will apply Topic Maps technology to model relationships between items. Topic Maps related technologies are used in different research work. Dichev et al. [5] try to use Topic Maps to organize and retrieve online information in the context of e-learning courseware. They think Topic Maps offers a standard-based approach for expert's knowledge. This allows further reusing, sharing and interoperability of knowledge and teaching units between courseware authors and developers. Dong and Li [6] propose a new set of hyper-graph operations on XTM (XML Topic Map), called HyO-XTM, to manage the distributed knowledge resources. In the HyO-XTM, the set of vertices is the union of the vertices and the hyper-edges' sets of the hyper-graph; the set of edges is defined by the relation of incidence between vertices and hyper-edges of the hyper-graph. The hyper-graph model matches the Topic Maps with Hyper-graph vertices mapping to topic nodes and edges mapping to association nodes. Topic Maps is shown to be a new way to graphically manage the knowledge. Based on the previous work, we will first time try to use a topic map to represent relationships among items of recommender systems, so as to be aware of the relationships of items.

3 Topic Maps Based Trusted Recommender Model

We propose a graphical conceptual model for recommender systems, in which we describe three types of nodes, i.e., user nodes, item nodes, and topic nodesIn this model we also consider three types of relationships: *trust* (from one user to another), *rating* (from a user to an item), and *belonging* (from an item to a topic), see Fig. 1.

3.1 Model Description

We use a user graph $G(V,E)$ to model the user trust network, where V is a set of user nodes, representing users, and E a set of directed edges, representing *trust* relationships, see Fig. 1 (left). A trust relationship $e \in E$, is an edge in G, from a user node v_i

to another user node v_j. Each e in E is associated to a value in [-1, 1], indicating the weight of e. A negative trust value between two users means that they distrust each other and a positive trust value means that they trust each other. We use $e(v_i, v_j)$ to denote the trust value. We define a *truster* function of a user node v, yielding the set of all the users who have a trust relationship (an edge) to v, as $truster(v) = \{\forall u \in V \mid (u,v) \in E\}$. We also define a *trustee* function of v, representing the set of all the users who have a trust relationship from v, as $trustee(v) = \{\forall u \in V \mid (v,u) \in E\}$. For each user node v, we define a reputation function, denoted as $\rho(v)$, taking values from [0, 1].

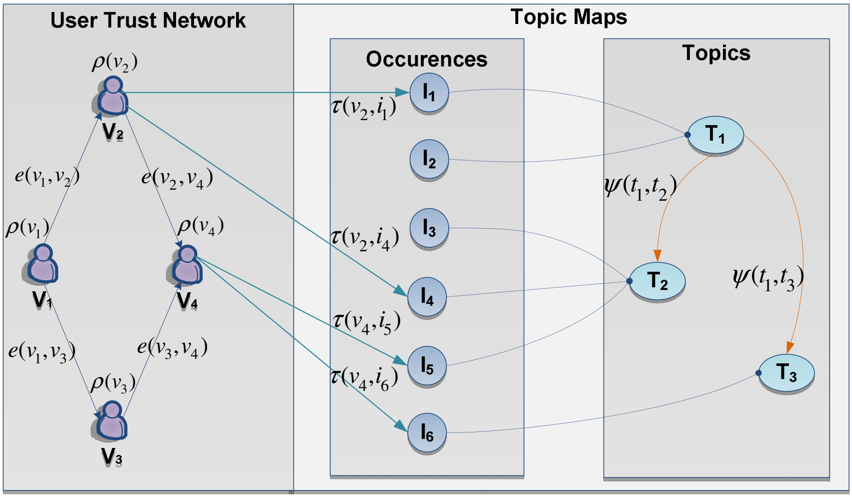

Fig. 1. Example of Topic Maps based trust recommender model – Users Trust Network (left) and Topic Maps (right)

Now we consider this type of relationships: *rating* R, from the user node set V to the item node set I. Each element $(v,i) \in R$ is an edge from a user who rates the item to the item with a rating function $\tau(v,i)$. We define the set of items rated by the user v by the function $item(v) = \{i \in I \mid (v,i) \in R\}$. Similarly, we use the function $reviewer(i) = \{v \in V \mid (v,i) \in R\}$ to represent the set of users who rate the item i.

According to the concept of Topic Maps, an item is an occurrence which belongs to a topic. We define the type of relationship, *belonging* B, from the item set I to the topic set T. Each element $(i,t) \in B$ is a direct edge from an item i to a topic t. An item might belong to a number of topics. So we use the function $topic(i) = \{t \in T \mid (i,t) \in B\}$ to define the set of all the topics the item i belongs to. We use the function $occurrence(t) = \{i \in I \mid (i,t) \in B\}$ to define the set of all the items belonging to the topic t. To model the association between topics in a topic map, we use a function $\psi(t_m,t_n)$ to represent the association degree between two topics t_m and t_n. Its value is a real number in [0, 1]. The higher the value is, the closer the two topics are.

3.2 Topic Maps Based Trusted Recommendation Methods

Using Topic Maps, we conceptually describe users, items, and topics, as well as various relationships between them. In this section we will introduce a computation method to quantitatively calculate these functions defined on the nodes and relationships.

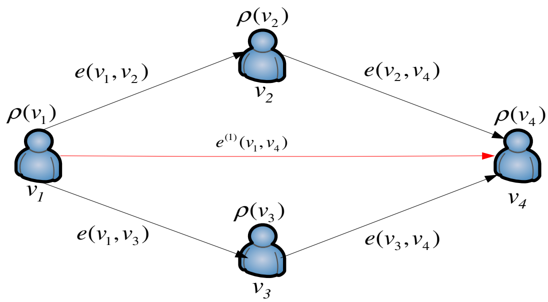

Fig. 2. Example of trust propagation

3.3 Trust Model

In the trust model, the trust relationships among users are the basic ones, from which we derive users' reputations and propagate new trust relationships among users. The reputation of a user v is computed by averaging all the trust values of the trust relationships to v from other users, i.e.

$$\rho(v) = \left(\sum_{u \in truster(v)} e(u, v) \right) \Big/ |truster(v)| \tag{1}$$

If a user has no trust relationship from a truster, its reputation is set to 0. However, for any two users u, v if they do not have a direct edge (i.e. trust relationship) between them but have indirect edges (i.e. via one more users), we use trust propagation to determine the trust value between u, v. In other words, we aim to use existing values in the trust network to gain more trust values between the users without direct trust relationships. For simplicity, we only consider to propagate trust relationships but not distrust relationships in this paper. We use a step-by-step trust transitivity to derive indirect trust, in which a single step means to derive trust by the intermediate user nodes which have direct edge to both the start user node and the target user node in the user trust network, see Fig. 2. We use solid lines to represent existing trust relationships among users and dashed lines to represent the derived trust relationship. The trust relationships between v_1 to v_4 can be derived in the first single transitivity of trust propagation and that between v_1 and v_5 can be derived in the second single transitivity. In order to clearly explain the propagation process of trust, we use $e^{(n)}(v_i, v_j)$ to denote a *newly derived* trust value in the nth single step of trust transitivity. The original trust value $e(v_i, v_j)$ is denoted as $e^{(0)}(v_i, v_j)$, which means the existed trust edges in the original trust network.

For example, to derive a new trust value from the user node v_1 to the user node v_4, there might be a number of paths, where a path means a chain of edges from v_1 to v_4 via an intermediate user node, e.g. v_2. Here we define a function for the set of the common user nodes as $com(v_i, v_j) = trustee(v_i) \cap truster(v_j)$. We consider all the paths to derive the trust value:

$$e^{(n+1)}(v_i,v_j)=\frac{\sum_{v_k\in\left(trustee(v_i)\bigcap truster(v_j)\right)}(e^{(\{0,1,2,\ldots n\})}(v_i,v_k)\times\rho(v_k)+e^{(\{0,1,2,\ldots n\})}(v_k,v_j)\times\rho(v_j))}{\sum_{v_k\in\left(trustee(v_i)\bigcap truster(v_j)\right)}(|\rho(v_k)|+|\rho(v_j)|)} \quad (2)$$

Here, $e^{(\{0,1,2,\ldots n\})}(v_i,v_k)$ is a trust relationship in the set of all the trust relationships including the original trust relationships and those generated in the 1st, 2nd,…, and nth step of the single step transitivity. The formula above gives a new trust value in [-1, 1] by applying once the single step transitivity. For a trust network, we can propagate trust relationships using a number of steps of the single step transitivity. We use a parameter s to control the number of steps for trust propagation.

3.4 Deriving Users' Opinion Based on the User Trust Network

In this section, we discuss how to generate a rating value between a user and an item if there was none there. We use the trust values from the user trust network and the rating values from the existing ratings given by the users to the items to derive users' new opinions on items together with new rating values. We denote the newly generated rating relationships through the user trust network as R'. We indirectly compute users' opinion on items through rating on the items from the intermediate users if they rated them directly. These intermediate users should have positive reputation values. The users with negative reputation values are thought as malicious users and not allowed to give advices to others. The newly generated rating relationships with rating values are computed by the function τ' given below.

$$\tau'(v,i)=\left(\sum_{\mu\in trustee(v)\bigcap reviewer(i)} e^{(\{0,1,2,\ldots n\})}(v,\mu)\times\tau(\mu,i)\times\rho(u)\right)\Bigg/\sum_{trustee(v)\bigcap reviewer(i)}\rho(u) \quad (3)$$

3.5 Deriving User's Opinion Based Topic Maps

In section 3.4 we generated a new set R' of rating relationships using trust propagation on the user trust network in the section 3.4. However, if the user trust network contains a lot of isolated clusters, the trust values and rating values from one cluster would not be possible to be used for other clusters. We call this the isolated trust cluster problem and will further explain it in section 4.1.

Here we consider using the Topic Maps to solve this problem. We use the topic map to derive users' opinion on topics. To do so, we first define a function $g(v, t)$ to be an user v's opinion on a topic t, deriving from users' opinion on the items and items belonging to the topic t, as follows:

$$g(v,t) = \left(\sum_{i \in item(v) \cap occurrences(t)} \tau(v,i) \right) \Big/ |item(v) \cap occurrences(t)| \quad (4)$$

Let us consider how to construct a topic map for a recommender system. We adopt association rule for building the association relationships between topics, because the association rule is frequently used to investigate sales transactions in market basket analysis and navigation paths within websites [24]. We define a function $\psi(t_m, t_n)$ to measure associations between the topics t_m and t_n, in terms of the users who have rated the topics, as follows:

$$\psi(t_m, t_n) = |user(t_m) \cap user(t_n)| \,/\, |user(t_m)| \quad (5)$$

In formula (5), the function $user(t)$ represents the set of users who rated the topic t. We set a threshold, denoted as *confidence* θ, to be used in **filtering out** the associations with value less than the threshold. The associations after filtering can be used to derive users' opinion on a topic which they did not rate. The computation formula is as follows:

$$g(v,t) = \frac{\sum_{t_m \in \{t \in T | g(v,t) \neq 0, \psi(t_m,t) \neq 0\}} g(v,t_m) \times \psi(t_m,t)}{|\{t \in T \mid g(v,t) \neq 0, \psi(t_m,t) \neq 0\}|} \quad (6)$$

Finally, we consider how to decide a user's opinion on an item through both trust and topic map. We use a combination of users' opinion derived based on the topic map and users' opinion on items, to compute users' opinion $\tau'(v,i)$ based on the user trust network.

$$\tau'(v,i) = (1-\varphi) \times \tau(v,i) + \varphi \times \left(\left(\sum_{t \in topic(i)} g(v,t) \right) \Big/ |topic(i)| \right) \quad (7)$$

Here, φ is a weight parameter in [0, 1] to help controlling the weight of implicit opinion by themselves on an item, i.e., the weight of user's own opinion.

4 Experiments

In this section, first we describe the dataset used in our experiments, and then we discuss the experiments and their results.

4.1 Dataset

We use a data collection of the real review data from Epinions.com, provided at Massa's website [16], as the input dataset. We use two datasets, the trust relationships (and their values) between users and the users' ratings on items (and their values). In order to reduce the time and space complexities of algorithm, we use two subsets obtained by the method described below:

- Extract all the users in the first dataset and select 100 different users.
- Extract all the trust relationships among the 100 users. We obtained a subset, called subset 1. It contains 110 trust relationships, 82 of which have trust value 1 and 28 have trust value -1.
- Extract all the ratings given by the 100 users in the second dataset. We first obtain 282418 ratings on 230126 items from the 64 users who rated the items. Through sampling the ratings, we obtain the subset 2. It contains 10141 ratings, with 8858 items and 34 users. The subset 2 has 6 different levels of rating values and 27 topics. As shown in Figure 3, most items are rated 5 and 4. Only a small proportion of them are rated 1, 2, 3 and 6.

From the sample datasets we constructed for the experiments, we clearly observe the problems of "data sparsity" and "cold start users", which we discussed in Section 1. There are 10141 ratings for 100 users and 8858 items in this recommender system. So the subset of this recommender system is sparse because the ratio of the number of ratings to the total number of the matrix (number of users times number of items) is 10141/(100*8858)= 1.14%. Only one out of 100 users rated some items, so there are more than 98 cold start users. The maximum ratings for one user is 7507, on average every user 101 ratings.

The trust relationships in the subset 1 form a user trust network, as shown in Fig. 4. We use the trust propagation method discussed in section 3 to obtain more trust relationships. But this user trust network consists of many "isolated trust clusters". They do not connect to each other and contribute little to the trust propagation computation.

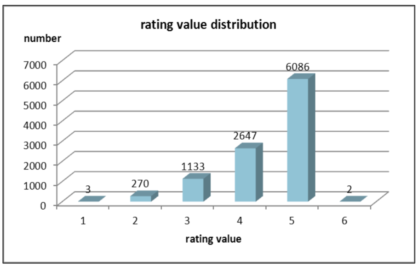

Fig. 3. The distribution of rating values

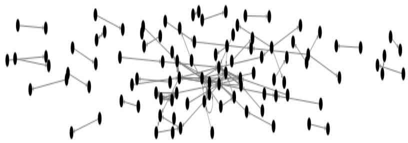

Fig. 4. The structure of user trust network

4.2 Results

We use MAE (Mean Absolute Error) and MAUE (Mean Absolute User Error) [15] to evaluate our recommendation method, because the MAE is the most commonly used and the easiest to be understood, and based on MAE, the MAUE provides the averages of evaluation.

Based on the observation that the most derived trust values have been obtained in the first three steps of trust propagation on the user trust network, we consider to set *s*=3. We evaluate the variation of accuracy as the weight parameter changes with a *confidence* θ =0.95 in constructing a topic map. As show in Fig. 5, both the MAE and MAUE decline nearly in a straight line with the weight parameter. We can see that the MAUE is always less than the MAE due to the many cold start users in our dataset. So we find that the two metrics keep consistent in the relationship between accuracy and weight parameter.

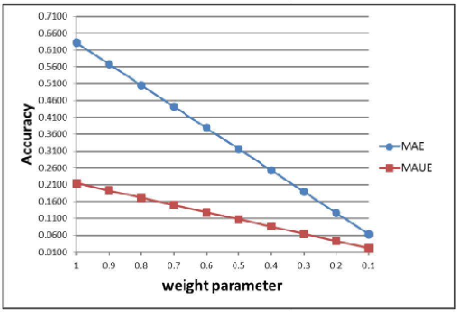

Fig. 5. The variation of accuracy with weight parameter

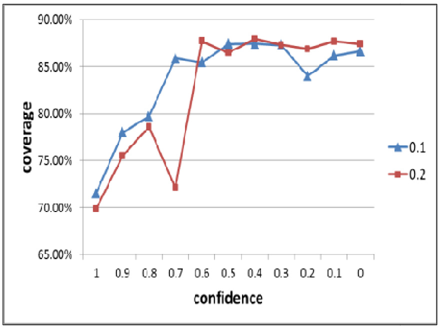

Fig. 6. The coverage changing as confidence of Topic Map

Furthermore, we consider using coverage to measure the performance of our method. First we set the weight parameter φ to be 0.1 and 0.2 respectively. We select the top 10 most-suited items in the recommendation lists of items. In Fig. 6, the line named 0.1 represents the coverage with the weight parameter φ to be 0.1 and the line named 0.2 represents the coverage with the weight parameter φ to be 0.2. As the confidence θ decreases from 1 to 0, the coverage rises. The coverage in the two lines rises sharply when the confidence is 0.7 and then it does not vary considerably. The reason for the changing of coverage is that when the confidence θ becomes smaller, the topic map will give more association relationships between topics to support deriving users' opinions on items. The result tells that the Topic Maps does help improve the coverage of recommender systems.

5 Conclusion and Future Work

We have three contributions in this work. First we propose a trust model based on the user trust network and a method to compute the trust propagation. We use the reputation as the weight in trust propagation, which mimics considering friends' advices before people buying products or services in the real world. That is, advices from the users with the greater reputation values are trusted by their friends with higher degree. Second we propose a recommendation method, applying Topic Maps in analyzing users' opinions on topics, which better and further supports deriving users' opinions on items. Third we evaluate our method using the two metrics accuracy and coverage.

The result tells that the recommender system based on our method provides better accuracy and coverage in coping with the problems of the sparsity and cold start users.

For the next step of study, we plan to scale up our method for recommender systems to a reasonably large number of users in the user trust network as in the reality a recommender system should be able to deal with millions of users and hundred millions of items. We also consider to include the computation of distrust relationships in the trust propagation method as we believe it will greatly contribute to the accuracy and coverage of recommender systems.

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