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RESEARCH ARTICLE OPEN ACCESS

TRUST AWARE RECOMMENDATION USING DEEP MATRIX FACTORIZATION MODEL

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ABSTRACT

Recommender Systems, a critical tool in the field of information filtering, have recently undergone extensive research and development in both academic institutions and business. But the majority of today's recommender systems struggle with the following issues: (1) The user-item matrix's huge scale and sparse data need an impression on efficiency of recommendations. Therefore, the majority of recommender systems struggle to deal with customers who have left minimal ratings. It is sometimes discussed to as a taciturn jump issue. (2) The orthodox recommender methods considered the independence and uniform distribution of all users. This presumption ignores any user connections, which is inconsistent with suggestions made in the real world. In order to more correctly and realistically represent recommender systems, we present a model with a new factor trust analysis that naturally takes into account the preferences of the users and their reliable friends. Therefore, Deep matrix factorization (DMF) technique incorporates both the unambiguous impact of reliable users on the forecast of items for an active user, building on top of a state-of-the-art recommendation algorithm, SVD++. The investigational outcomes exhibit that our approach outperforms cutting-edge skills in this context. Our research shows that modeling trust metrics significantly improves suggestion accuracy, Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and F-Measure parameter specially for users who are just starting out.

I. INTRODUCTION

Recommender techniques are a specific type of data cleansing process that help in providing recommendations for content or goods that are likely to be of interest to consumers and assist them in locating the right thing. Memory and model systems are the two most common forms of recommender systems that have been developed. Memory algorithms [1] analyze the user-item ranking matrix and make recommendations based on how many users' ranking profiles are most like to the user and how they rated item i. Model-based techniques simply save the factors that a prototypical has learned. As a result, after the model's factors have been learned, these approaches are very quick because no need to examine the rating matrix. The disadvantage of this method is the necessity for training, whereas memory-based systems do not require training but have a slower prediction (test) phase [2].

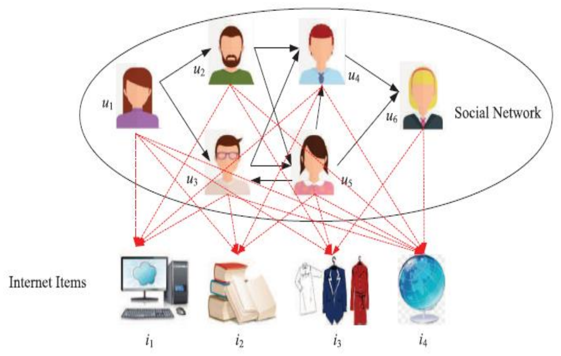
Although recommender methods have acknowledged a lot of scholarly consideration and have been used by companies like Amazon, Netflix, and eBay, the majority of these methods have a number of shortcomings. The first difficulty is that many collaborative filtering algorithms have trouble accommodating users who have only evaluated a small number of items due to the sparsity problem and taciturn jump problem [3]. Least number of ratings from fresh users, it is more difficult to identify similar individuals when using taciturn jump users. In the second issue, fresh customers only rate a minor integer of products, which causes a difficulty for recommendations. Second, conventional recommender algorithms disregard user trust or social connection

[4]. But in the real world, we routinely ask our trustworthy friends for book, music, or restaurant recommendations, and their recommendations have an impact on the favors we receive [5]. As a result, conventional recommender systems do not produce accurate results because they solely use the user-item ranking matrix. If a new customer is logged in to a social network, communal grid-based recommender systems can offer recommendations for that person. The findings of the tests in [6] and other related research demonstrate that a communal grid offers a further foundation of data that may be used to enhance the excellence of suggestions [7]. Therefore, communal grid organization and the user-item ranking matrix should both be considered in contemporary recommender systems. An online community where people voice their opinions on various products and build relationships with one another is known as a social rating network [8]. Social rating networks for recommendations have certain memory-based methods up for consideration. These techniques search the social network for a group of people that a user trusts (directly or indirectly), identify them, and provide recommendations by combining their ratings. These techniques leverage trust's transitivity to spread to social network's indirect neighbors. Memory-based techniques take longer to test than model-based techniques because they need to navigate the social network.

II. LITERATURE REVIEW

Given that social trust gives a different perspective on user preferences than item ratings [9], trust-aware recommender methods have been the theme of wide investigation up to this point [10]. The trust metric has really made traditional collaborative filtering algorithms significantly better. Here are a few of the several algorithms that have been created to build trust in communal charts. In order to determine the level of trust among performer pairs in a communal grid, Golbeck introduces the TidalTrust algorithm in [10]. As a result, trust estimates are distributed throughout the network using a modified breadth-first search. This approach practices trust standards that are expressly delivered by grid users. The weighted average of the trust ratings given to customer v by customers whom user u has already trusted, or user v's neighbors, constitutes the trust estimate from user u to user v. Similar to Golbeck's concept, [11],[12], created MoleTrust, which includes explicit user trust declarations and propagates trust via the grid in two phases. The graph initially becomes a directed acyclic graph when all cycles are eliminated. The trust standards are then transmitted to a source user u for another user v using a weighted mean of the trust values assigned to v by the trusted neighbors of u, similar to how Tidal-Trust does it. It has been suggested to use the Advogato [13] maximum flow trust metric to identify the people that other users in an online community trust. The number n, which represents the number of members to trust, is the input for the Advogato algorithm. The grid must be transformed in order to give the edges of the network dimensions; therefore, it must comprehend the network's entire structure. It does not calculate different levels of trust; it merely calculates the nodes to trust. For recommendations that are dependent on trust, this method is inappropriate [14]. suggests a TrustWalker, random walk approach that blends trust-based and item-based recommendation in order to avoid noisy data. TrustWalker takes into account ratings for both the target item and related goods. With an increase in the length of the walk, there is a higher chance that the rating of a comparable item will be used instead of the target item's rating. Both trust-based and item-based collaborative filtering recommendations are included in their system as special examples. They can calculate the confidence in the forecasts using the random walk model. Guo et al.'s [9] cluster-based recommendations are improved by combining likeness and trust trendy direction to address their short correctness and analysis problems. To accurately group cold-start users, they also used ratings and trust. A stochastic block model with social awareness is suggested by Jamali et al. In this concept, the users and the objects are divided into various groups inside the social rating network. Compared to rating prediction, this algorithm performs better when predicting links. SoRec, a method of social regularization, was first proposed by Ma et al. Here, they take into account social interactions' limitations [15]. They propose to make use of a shared user-feature matrix factored by trust and ratings. The social trust ensemble approach, RSTE, was then proposed by [16]. They first take into account a simple matrix factorization model in this before combining it with a trust-based locality theme. The user-specific vector of the active user is also indicated by these same authors [17] to be extremely adjacent to the normal trustworthy users. They created a fresh matrix factorization theme called SoReg using this concept as regularization. A strategy known as SocialMF was introduced by [17]. On top of SoReg, they designed SocialMF while taking trust propagation into account. They reformulated trusted user contributions in addition to item predictions to produce the user-specific vector for the active user [18],[19].

Memory-based techniques, however, can take a long time to search for potential neighbors in a wide user space and struggle to adapt to enormous data sets.



	i_1	i_2	i_3	i_4
u_1	4		4	3
u_2	3	4	4	3
u_3	2	5		3
u_4	5			
u_5	4	3	4	5
u_6		5	3	5

(b)

Figure 1: Trust Aware Recommendation System (a) Item-based-rating in Communal Grid (b) User-Item-based-rating.
Source: Authors, (2024).

III. METHODOLOGY

In this study, discuss collaborative filtering generally, and strategies to enhance its capacity to generate reliable recommendations in particular. We attempt to alter how recommendation partners are often chosen or given weight during the suggestion process. Specifically, that we believe that partner trustworthiness should be taken into account in accumulation to profile-to-profile relationship, which is the traditional basis for relationship assortment. Despite having ratings that are comparable to those of the target user, a recommendation partner may not be an accurate forecaster for a particular item or set of items. For instance, because we share similar tastes in movies, we frequently ask our friends for recommendations when choosing a movie to watch. However, a certain acquaintance might not be reliable when recommending a specific kind of film [20]. The key idea here is that partner similarity alone does not matter. Our recommendation partners should share our preferences and be trustworthy trendy direction to deliver endorsements that can be relied upon.

Here, two categories of trust: open trust and inherent trust. Open trust is a value or claim that is directly offered by users. Inherent trust is a relationship that is derived from other information that is readily available [21].

The communal connections that are related to less strong than communal trust connections are known as trust-alike relationships. Users who trust an active user are referred to as trusters, while users who are trusted by the current user are referred to as trustees [22].

There are four datasets with reliable information accessible. Epinions, Ciao, Filmtrust, and Flixter are among them. Epinions and Ciao are two databases with a wide range of objects. Film sets include Filmtrust and Flixter.

Ratings for the objects and trust values are the data in these databases. In general, this information is relatively scant. Asserts that ratings data and trust may be complementary. For improved outcomes, we will therefore take into account both implicit and explicit assessments. Because trust connections are asymmetric, it is not required to assume that if A trusts B, B also trusts A. This occurs because B could not believe that A is reliable. In communal grids, user A may independently join to a numeral of communal acquaintances as well as receive connections from other users. Therefore, in this social network, A's ratings may be influenced in both directions. Both the trustees and the trusters will have an impact on his rating. A recommendation model with both trustee and truster regularizers coupled has been proposed by [23], demonstrating the importance of trusters' effect.

In communal ranking grids, any user can create a social network by designating other users as trusted friends. The recommendation challenge in this study aims to forecast the ranking a user will offer a fresh item using previous item rankings and communal ranking grid trust data. For instance, to determine the worth of the ranking that user A will give to item P, both a user-item ranking matrix and a user-user trust matrix are required [24]. Consider, a recommender system which has m users and n items. Let the user–item rating matrix be R, where each entry in this matrix be, represent the ranking given by user u on item i. Hence, i can be any real number in the range of [1,5]. We represent users with symbols u, v and items with i, j. As users are rates only a minor share of items. The ranking matrix R is observed to be very sparse. Let the set of items rated by user u be. We utilize the matrix factorization technique to learn the hidden features of users and objects in order to forecast the unknown rankings using these hidden qualities. [25].

Learning these hidden variables and utilizing them for advice is the tenet of matrix factorization. Let s_u and t_i be a d-dimensional hidden feature direction of customer *u* and item *i*. These are 2 low rank matrices.

- user-feature matrix $S \in R_d \times m$
- Item-feature matrix $T \in R_d \times n$

The ranking matrix R, i.e., $R \approx S^T \cdot T$. Hence, $\bar{r}_{u,j} = t_j^T \cdot S_u$ The main aim of the recommendation method should be to forecast the ranking $\bar{r}_{u,j}$ near to the actual true value $r_{u,j}$. Formally, we can acquire the user- feature and item-feature matrices by minimizing the following loss function:

$$L_R = \frac{1}{2}\sum_{u}\sum_{j\in I_u}(t_j^T s_u - r_{u,j})^2 + \frac{\lambda}{2}\Big(\sum_{u}\|s_u\|_F^2 + \|t_j\|_F^2\Big) \qquad (1)$$

Where, λ is controls model complexity and avoids over-fitting. ‖.‖F is the Frobenius norm.

We will consider the communal grid here as it impacts the ranking value to be forecast. The communal grid can be represented by a graph $G=(V,E)$, where *V*= nodes as users. *E=edges* of the graph*. t* directed trust between two nodes. We use the adjacency matrix $X=[x_{u,v}]_{m\times m}$ to describe the structure of edges E. $t_{u,v}$ = value of trust relation between the nodes from users *u* to *v*.

The value of $t_{u,v}$ can be 1 or 0 which denotes either trust exists and does not exist from user *u* to *v*. Same as ranking matrix trust matrix is very sparse. We apply matrix factorization method on the matrix *X* to get the 2 d-dimensional latent feature vectors, one for trusted u and the other for trustee *v*. We denote these two vectors with s_u and q_v respectively. In order to group them together, we believe that the active users in the ranking matrix and the trusters in the trust matrix share the same user-feature space. Hence, we have truster–feature matrix $S_{d\times m}$ and trustee–feature matrix $Q_{m\times d}$. Now, we can recover trust matrix *X* by $X \approx S^T \times Q$. Hence, a trust relationship can be anticipated by the inner product of a truster-specific vector and a trustee-specific vector $\bar{x}_{u,v} = q_v^T \cdot s_u$. It is possible to learn the matrices *S* and *Q* by minimizing the subsequent loss function:

$$L_x = \frac{1}{2}\sum_{u}\sum_{v\in X_u^+}(q_v^T \cdot s_u - x_{u,v})^2 + \frac{\lambda}{2}\Big(\sum_{u}\|s_u\|_F^2 + \sum_{v}\|q_v\|_F^2\Big) \qquad (2)$$

Where, X_u^+ = set of customers trusted by customer *u*. It is the set of out-going trusted customers. Our trust aware model is built up considering a state-of-the-art model known as *SVD++* proposed by Koren. The *SVD++* considers *user/item* biases and the influence of rated items other than *user/ item-specific vectors* on ranking forecast. Formally, the ranking for customer *u* on item *j* is projected by,

$$\bar{r}_{u,j} = b_u + b_j + \alpha + t_j^T\Big(s_u + |I_u|^{-\frac{1}{2}}\sum_{i\in I_u} y_i\Big) \qquad (3)$$

Here b_u, b_j = assessment bias of customer *u* and item *j*. α = global average rating. y_i represents the inherent impact of items rated by customer *u* in the previous on the assessments of unidentified substances. Thus, customer u's feature vector can be also represented by the set of items the rated, and so it is modelled as $(s_u + |I_u|^{-\frac{1}{2}}\sum_{i\in I_u} y_i)$.

Adding Implicit influence of Trust:

An active customer can have many trusted customers and while calculating ranking of he on item j. The aggregate of the rankings given by his trusted customers can add impact on his ranking because of the likeness of him and the trusted customers. This can be represented as follows

$$\bar{r}_{u,j} = b_{u,j} + t_j^T (s_u + |I|^{\frac{-1}{2}} \sum_{i \in I_u} y_i + |X_u^+|^{\frac{-1}{2}} \sum_{v \in X_u^+} q_v) \quad (4)$$

Where, $b_{u,j} = b_u + b_j + \alpha$, represents bias terms, q_v is the customer i.e. trustee-specific hidden feature direction trustworthy by customer u, and hence $t_j^T q_v$ can be understood as an impact of trustees when we calculate ranking forecast by customer *u* on *j*. Thus, feature vector for customer *u* is understood by the trust he has on the set of his trustees i.e. and the set of items he rated before. Therefore, it is modeled as

$$(s_u + |I|^{\frac{-1}{2}} \sum_{i \in I_u} y_i + |X_u^+|^{\frac{-1}{2}} \sum_{v \in X_u^+} q_v)$$

With the impact of inherent trust the objective function to minimize is given by as follows:

$$L = \frac{1}{2} \sum \sum (\bar{r}_{u,j} - r_{u,j})^2 + \frac{\lambda}{2} (\sum_u b_u^2 + \sum_j b_j^2 + \sum_u \|s_u\|_F^2 + \sum_j \|t_j\|_F^2 + \sum_i \|y_i\|_F^2 + \sum_v \|q_v\|_F^2) \quad (5)$$

Here $\bar{r}_{u,j}$ is calculated by equation (4).

Deep Matrix Factorization Method:

Algorithm 1 provides the model's pseudocode. Inputs such as the user item ranking matrix R, the customer trust matrix *X*, the initial learning rate, and the regularization factor are required here. We start by setting tiny beginning values for the low-dimensional feature vectors that make up the matrix factorization approach. The loss function has converged, the model training once process is completed. The gradient descent method is used in this to compute gradients for all variables and update their values in each step [27]. Then learnt matrices and vectors are returned, which are utilized to forecast the new rating that is needed.

Algorithm: Proposed Algorithm
Steps:

1. *Take inputs matrix R, matrix X, λ,γ;*
2. *Initialize matrices S, T, Q, vectors I_u, X+, B_u, B_j;*
3. *Initialize parameters iterations, number of features d;*
4. *Repeat*
5. *Compute gradient for all the variables in equation 5;*
6. *$b_u = b_u - \gamma \partial L/(\partial b_u)$, u=1 to m*
7. *$b_j = b_j - \gamma \partial L/(\partial b_j)$, j= 1 to n*
8. *$s_u = s_u - \gamma \partial L/(\partial s_u)$, u= 1 to m*
9. *$t_j = t_j - \gamma \partial L/\partial t_j$, j=1 to n*
10. *for all i϶ I_u, $y_i = y_i - \gamma \partial L/(\partial y_i)$, u= 1 to m*
11. *for all v϶ T_u+, $q_v = q_v - \gamma \partial L/(\partial T_u+)$, u=1 to m*
12. *Until convergence*
13. *Return B_u, B_j ,S, T, Q;.*

IV. RESULTS AND DISCUSSIONS

Evaluation Parameter:

We used two measures, the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE), to compare the prediction quality of our proposed method to earlier collaborative filtering and trust-aware recommendation systems.

1.**The metrics MAE is well-defined as**

$$MAE = \frac{\sum_{u,i} |\bar{r}_{u,i} - r_{u,i}|}{N} \quad (6)$$

Here $\bar{r}_{u,i}$ denotes the rating user *u* gave to item *i* predicted by any model and $r_{u,i}$ is the actual rating user *u* gave to item *i* and *N* denotes the number of tested ratings.

2.**The metrics RMSE is well-defined as**

$$RMSE = \sqrt{\frac{\sum_{u,i} (\bar{r}_{u,i} - r_{u,i})^2}{N}} \quad (7)$$

As MAE and RMSE decrease the performance of the model is considered high which means the smaller values of them show better accuracy.

3.**The metrics F-Measure is well-defined as**

$$F_M = \frac{(2 \times precision \times recall)}{(precision + recall)} \quad (8)$$

Dataset used for Deep Matrix Factorization Method:

Since publicly accessible, relevant datasets are uncommon in the field of trust-aware recommendations, we primarily use the following methods:

1) **Epinions:** Epinions, which has 139 738 items and 49 290 users, is publicly accessible. In Epinions, there are 664 824 ratings and 487 181 trust relationships, respectively. The rating system ranges from 1 to 5. I use these records to create a network of social trust. Every user on Epinions maintains a connection of trust with others. Additionally, fewer than 0.01% of the user-item rating matrix is dense [28].

2) **Flixster:** This communal grid enables people to give movies ratings. It has 492 359 different things that have been rated by its 1 049 445 consumers. There are 8 238 597 reviews in all. There are 26 771 123 trust ties in all. The rating matrix's density is less than 0.0016% [28].

Experimental Results:

Table 1: Comparison of proposed method with other approach using rmse parameter on epinions and flixster datasets.

	Algorithm	RMSE	
		Epinions	Flixster
1	UserCF	1.38785	0.8725
2	ItemCF	1.39457	0.9167
3	MoleTrust	1.24587	0.9087
4	TidalTrust	1.27485	0.8425
5	BMF	1.22001	0.8041
6	STE	1.10445	0.8422
7	Random Forest	1.09254	0.8273
8	PCA	1.09222	0.7922
9	NLRDMF-TD	1.07452	0.7452
10	**Deep Matrix Factorization (DMF)**	**1.02452**	**0.7229**

Source: Authors, (2024).

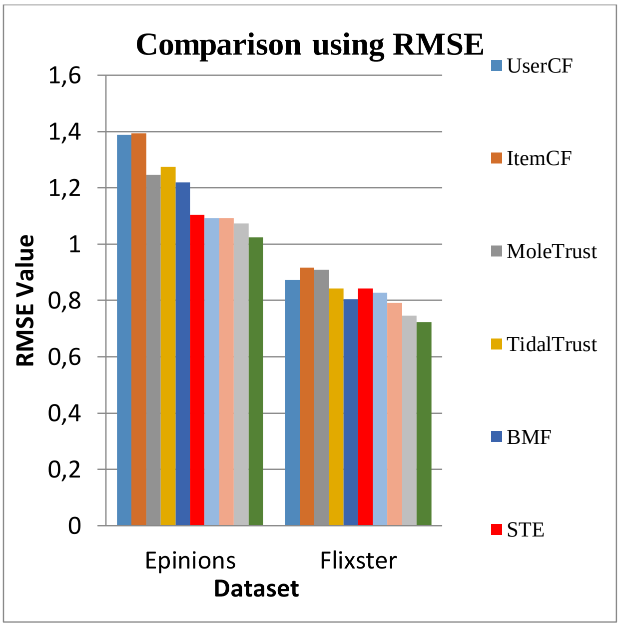


Figure 2: Comparison using RMSE Parameter.
Source: Authors, (2024).

Table 2: Comparison of proposed method with other approach using mae parameter on epinions and flixster datasets.

Sr. No	Algorithm	MAE	
		Epinions	Flixster
1	UserCF	0.5846	0.6646
2	ItemCF	0.5124	0.6129
3	MoleTrust	0.4866	0.5826
4	TidalTrust	0.4621	0.5647
5	BMF	0.5972	0.5442
6	STE	0.4435	0.4965
7	Random Forest	0.3892	0.4849
8	PCA	0.3622	0.4641
9	NLRDMF-TD	0.3424	0.4364
10	Deep Matrix Factorization (DMF)	**0.3124**	**0.4168**

Source: Authors, (2024).

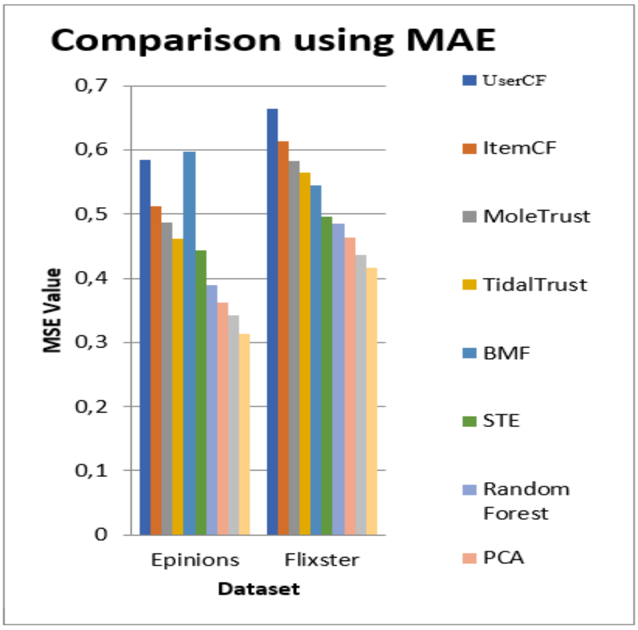


Figure 3: Comparison using MSE Parameter.
Source: Authors, (2024).

Table I and Table II, show in detail description about the experimental performance of Deep Matrix Factorization (DMF) with state-of arts. The DMF shows improvement in the results value in terms of RMSE, MAE and F-measure evaluation parameter.

Table 3: Comparison of proposed method with other approach using F-measure parameter on Epinions and Flixster Datasets.

Sr. No	Algorithm	F-Measure	
		Epinions	Flixster
1	UserCF	0.2846	0.7095
2	ItemCF	0.3134	0.7318
3	MoleTrust	0.4824	0.7742
4	TidalTrust	0.4821	0.8355
5	BMF	0.6972	0.8486
6	STE	0.7429	0.8546
7	Random Forest	0.7862	0.8665
8	PCA	0.8024	0.8752
9	NLRDMF-TD	0.8224	0.8749
10	Deep Matrix Factorization (DMF)	**0.8542**	**0.9024**

Source: Authors, (2024).

V. CONCLUSIONS

The suggested trust-based matrix factorization model in this paper takes into account both rating and trust data. Despite the fact that both matrices are fairly sparse, ratings and trust work best when combined to produce suggestions that are more accurate. In order to forecast ratings for unidentified things, our innovative method takes into account both the open and inherent influence of rankings as well as the inherent impact of trust evidence. In this paradigm, the trust influence of the active user's trustees is present. The model's computational complexity reveals whether or not it can handle massive data sets.

The suggested model for ranking prediction performs well because it combines trust and influence. Future research can examine the explicit and implicit effects that trust has on an item's rating score.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Pradip Mukundrao Paithane.
Methodology: Pradip Mukundrao Paithane.
Investigation: Pradip Mukundrao Paithane.
Discussion of results: Pradip Mukundrao Paithane.
Writing – Original Draft: Pradip Mukundrao Paithane.
Approval of the final text: Pradip Mukundrao Paithane.

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