International Journal For Recent Developments in Science & Technology
2581-4575
Crossref
A Peer Reviewed Research Journal

L-INJECTION: UNINTERESTING ITEMS TOWARD EFFECTIVE COLLABORATIVE FILTERING

[1]M. SESHU BHAVANI, [2]P. TEJASWI, [3]P. RESHMA CHOWDARY, [4]V. SINDHU TEJA SREE
[1]ASSOCIATE PROFESSOR, CSE DEPARTMENT, NRI INSTITUTE OF TECHNOLOGY, POTHAVARAPPADU
[2,3,4]UG STUDENT, CSE DEPARTMENT, NRI INSTITUTE OF TECHNOLOGY, POTHAVARAPPADU

Abstract: We are developing a new framework, called L injection, to address the problem of the availability of recommendation systems. By carefully injecting low values into a specific set of pairs of user elements not classified in the user object matrix, we demonstrate that the accuracy of Recommendation N Recommendations to many collaborative filtering (CF) techniques can be significantly improved and consistent. First we adopt the idea of user preferences before using it for a large number of unclassified elements. Using this idea, we identify uninteresting elements that have not yet been evaluated but are likely to receive low user ratings, and we will selectively select them as low values. Since our proposed approach is an inappropriate method, it can be easily applied to a variety of CF algorithms. We demonstrate that our solution consistently and globally reinforces existing CF algorithms (such as CF based on CF elements, SVD based on CFD and SVD + +)
2.5 to 5 times on average. In addition, the execution time of our CF methods improves from 1.2 to 2.3 times.

Keywords: Recommender System, Collaborative Filtering, Singular Value Decomposition(SVD), Cold Start Problem, Data Sparsity.

1.INTRODUCTION

Recommender systems (RS) aim to suggest essential items (e.g., movies, books, or news articles) to a user by analysing her prior preferences. Businesses face a critical problem as a huge number of online applications use RS as a vital component. RS uses several filtering techniques, among them collaborative filtering methods are the effective ones, based on the past behaviour of users such as explicit user ratings and implicit click logs, CF methods exploit the similarities between users' behaviour patterns. The problem here is the number of known ratings in the user-item matrix are very small in number, which is called data sparsity problem. As the user ratings plays a crucial role in recommendations ultimately CF methods suffer from the data sparsity. It is common for an e-business to have cold- start users which means many users buy items and very few items are rated. The goal of this work is to improve top N recommendation accuracies of CF methods by minimizing the data sparsity problem. Our proposal is based on the following hypothesis in CF: Let ratings say R, that

shows the satisfaction of users. Therefore, users tend to rate (high) only the items that they like, and those who are dissatisfied tend not to rate items in R. Then how can we identify the unknown opinions of those users who were dissatisfied and didn't leave ratings for items? To answer this question, note that unrated items in R can be classified into three different types: (1) unrated items whose existence users were not aware of, (2) unrated items that users knew and purchased but did not rate, and (3) unrated items that users knew but didn't like and thus didn't purchase. We note that the unrated items of the third type, called uninteresting items. Clearly indicate users' latent negative preferences on them. Therefore, it is better not to recommend those uninteresting items. In order to identify such uninteresting items,

2581-4575
International Journal For Recent Developments in Science & Technology
Crossref
A Peer Reviewed Research Journal

we propose to use a new notion of pre-use preference, i.e., an impression of items before purchasing and using them. That is, by definition, uninteresting items indicate the items with low pre-use preferences. Unfortunately, the ratings in R do not indicate pre-use preferences but the preferences after using the items, called post-use preference.

2. RELATED WORK

As the number of unrated items are more than the rated items it is difficult for the recommender systems to predict the items for the users. In the existing system for recommending items to the users, the CF methods used to consider the clicks and bookmarks. The main disadvantage of this existing system is, it creates extra collection of data which leads to sparsity problem again. Here in the term L-injection, L stands for low value. In the existing system, if there appears an unrated item cell in the user-item matrix, we simply consider zero as its value that is, 0-injection which means the item is an uninterested item and we simply ignore the item. The disadvantage of doing so leads to ignorance of genuine products and thus the uninteresting items are not effectively filtered. Though the item is rated for negligible number of times and gets high rating, in this scenario we need to observe that the particular item do not come under an uninteresting item but in the existing system we consider it as an uninteresting item. This means though the product or item is effective, genuine, well performed, if it is with no rating, we do not consider it for further recommendations. This is another drawback of the existing system.

3. METHODOLOGY

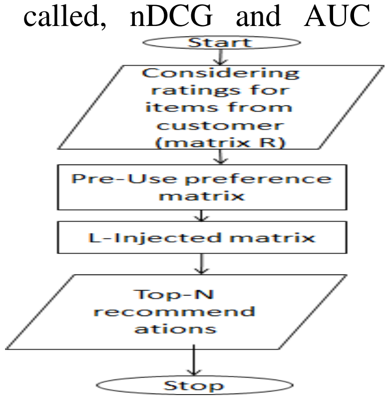
The CF methods we use has the following two steps:

(1) predicting the ratings of unrated items, and
(2) recommending top-*N* unrated appealing items to users

The main aim of proposed approach focuses on the minimization of sparsity problem which results in accurate top-n recommendations by filtering the uninteresting items. The proposed approach involves L-Injection, where L is some value. Instead of considering the unrated value as zero we inject some minimum low value in the user-item matrix. This injection of low value can be done by using Singular Value Decomposition (SVD) algorithm. It is one of the algorithms we use in the collaborative filtering techniques. How this technique works for injecting low values? In the step one, we consider a matrix where rows represent users and columns represent the items and the cells of the matrix are filled with the ratings given to the items by the users. In the step two, we build an augmented matrix where some missing entries are imputed by low values if their corresponding items are considered uninteresting. The augmented matrix can be applied to any CF method (thus making our approach method-agnostic), which enables existing CF methods to benefit from uninteresting items in their top-N recommendation.We compare several ways of applying low values for unimportant elements. The main method is to pump zero for uninterested elements, that is, vri = 0, which is suggested in our preliminary work [1]. Instead, we use the global average ratings and the average ratings for each user / item. Since articles are not likely to be interested in preference, their rankings should be set relatively low. We inject a value averaging the mean, vui = mean x δ × [0.25, 0.50, 0.75, 1.00].Precision ICF and SVD with injection matrix L. To construct the matrix L injected L, different

International Journal For Recent Developments in Science & Technology
2581-4575
Crossref
A Peer Reviewed Research Journal

calculation methods can be used. Gray indicates the best resolution for δ and θ. In both algorithms, the methods for calculating the use of averages exceed the use of zero. When δ = 0.5, it shows the best performance regardless of θ. Meanwhile, when δ <0.5 or 0.5> 0.5, the accuracy of ICF and SVD decreases. This means that users can rate items that are not interested in relatively low values, but will not hate them much if they are classified. We performed a sensitivity test to evaluate the effect that shows a greater precision of Recommendation N (N = 5) with ICF and SVD when varying. We increase θ with a 10% increase in the range of 10-90%, while increasing θ with a 1% increase for two extremes, 0-10% and 90-99.7%. Note that we do not report the result with θ = 100% because the CF methods with our approach do not recommend anything in this case. The result at θ = 0% indicates the accuracy of the original ICF and SVD methods without using our approach. Meanwhile, when setting up to 99.7%, we only leave the N main elements for which the pre-use preference scores are the highest for each user. In this case, all the remaining elements are chosen as the list of topN recommendations (that is, the top 5) for each user without using CF methods. We note that the precision results, called, nDCG and AUC show



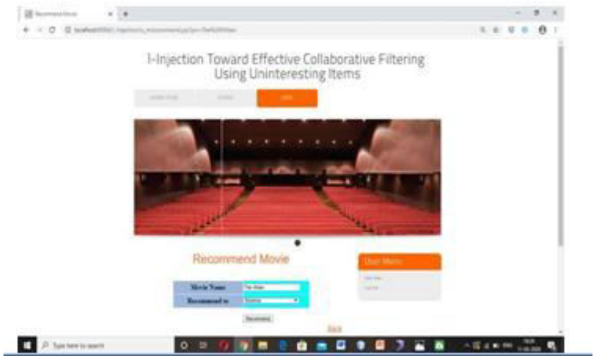
similar patterns. The accuracy of all cystic fibrosis methods increases with an increase of θ to approximately 95%. In addition, it grows very quickly to reach 10%. All results clearly show that our idea of using 1 injection significantly improved the accuracy of two original methods of cystic fibrosis. ICF using our approach with 96 = 96% shows better accuracy, 5.2 times greater than ICF without our approach. Similarly, when θ = 95%, our approach improves SVD accuracy by 3.4 times. We suggest a new approach, the L injection, for items that are not interested in using a new idea of pre-use preferences. This approach not only significantly reduces the problem of data asymmetry, but also prevents those elements of interest from being recommended. Since the proposed approach is not appropriate for the media, it can easily be applied to a wide range of existing CF methods. Through extensive trials, we have successfully demonstrated that the proposed approach is effective and practical, which greatly improves the accuracy of current CF methods (such as element-based CF, SVD- based CF and SVD + +) 2.5 to 5 times. In addition, our CF runtime approach improves from 1.2 to 2.3 times when your configuration produces the best accuracy.

Advantages

- Sparsity problem can be addressed.
- Identifying Uninteresting Items in efficient way.
- In this system an individual user can recommend products to another user personally.
- Interesting and uninteresting items can be separated based on previous searches and purchases.
- Justice for genuine products.

2581-4575
International Journal For Recent Developments in Science & Technology
Crossref
A Peer Reviewed Research Journal

Process Diagram



4. RESULTS

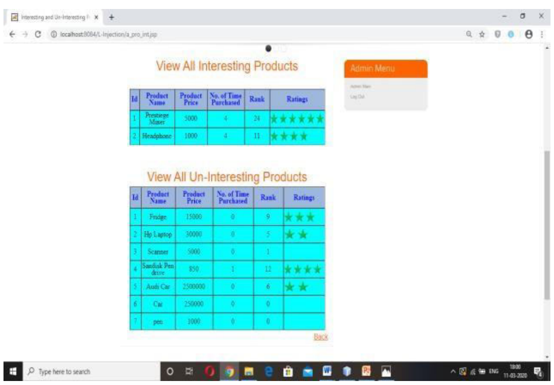


Fig: All interesting and uninteresting products

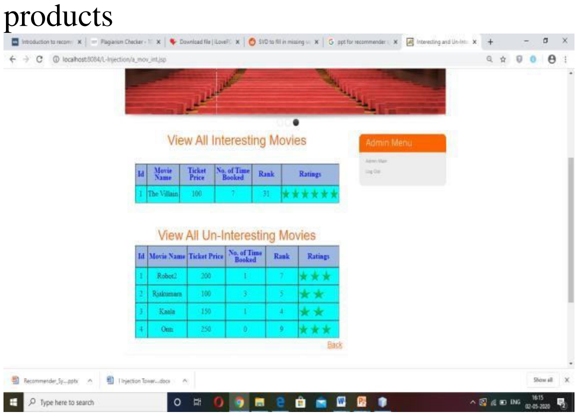


Fig: All interesting and uninteresting movies

Fig: An individual recommending to another

5. CONCLUSION

In the existing system the huge amount of data present, is difficult to analyse. Where as in our system we are able to separate both the interesting items and uninteresting items based on number of searches. Individual user can recommend products and movies to the other user. we demonstrate that our solution consistently and globally reinforces existing CF algorithms (such as CF based on CF elements, SVD based on CFD and SVD + +) 2.5 to 5 times On average In addition, the execution time of our CF methods improves from 1.2 to 2.3 times when your configuration produces the best accuracy.

6. FUTURE ENHANCEMENT

The proposed approach worked out well in improving the accuracy and minimizing the sparsity problem. The future enhancement of this work can bring out improved results by using interest injection (CSII), a method that can effectively find interesting, satisfying, and serendipitous items in unrated items.

REFERENCES

[1] W. Hwang, J. Parc, S. Kim, J. Lee, and D. Lee, “Told you i didn’t like it: Exploiting uninteresting items for effective collaborative filtering,” in Proc. of IEEE ICDE, 2016, pp. 349–360.

[2] G. Adomavicius and A. Tuzhilin, “Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions,” IEEE Transactions on Knowledge and Data Engineering, vol. 17, no. 6, pp. 734–749, 2005.

[3] Y. Koren et al., “Matrix factorization techniques for recommender systems,” IEEE Computer, vol. 42, no. 8, pp. 30–37, 2009.

[4] B. Sarwar et al., “Item-based collaboration filtering recommendation algorithms,” in Proc. of IEEE WWW, 2001, pp. 285–295.

[5] S. Zhang et al., “Using singular value decomposition approximation for collaborative filtering,” in Proc. of IEEE CEC, 2005, pp. 257–264.

2581-4575

International Journal For Recent Developments in Science & Technology

Crossref

A Peer Reviewed Research Journal