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A Secure Cold-Start Online Product Recommendation System with Reputation Defense Technique Using Anomaly Detection

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Abstract:**Connecting Social Media to E-Commerce System with Reputation System and making the proposed system more secure with Anomaly based technique. In the existing paper, the author proposed learning both clients' and products' feature representations from data collected from e-commerce websites. But they did not considered about the False Ratings or Misbehaving Clients/False client's value. The Concept of Reputation System was introduced to have a better outcome of a metric have encapsulating reputation for a particular domain for each identity within the system. This reputation systems objective is to produce an accurate assessment in the model of different factors but not to adversarial environments. Thus we make a particular focus on introducing the reputation system model into the existing system and propose a new secure model. The proposed system commenced to provide a secure framework that grants for general decomposition of existing reputation system model. Confident and Secure reputation modeling system is a vital aspect in managing risk and building customer satisfaction in e-commerce system. Miserable, the existing Cold start model does not considered the reputation model and uses only the simple feedbacks and comments issues from Online Social Networking client. Foresaid schemes are known easily to cheat/deceive and which also does not provide needed security or protection against several types of fraud/attacks. So we propose an anomaly detection technique for finding unfair recommendation in online Product Recommendation Model.**

Keywords: *E-commerce recommendation, Anomaly detection, similarity measures, preference feature construction.*

I. INTRODUCTION

In recent years with the speedy development of engineering and network technology, electronic commerce is being additional enterprises and people involved. However, as additional to provide the services, their structures are more advanced and which frequently cause clients lost an oversized range of commodities within the info area, couldn't realize their real desires. Currently, additional personalised recommendation technology has been of concern to students, representative of the recommended techniques are: Social networking based recommendation systems (SNB), Content filtering based recommendation systems (CB), Collaborative filtering based recommendation systems (CF), Knowledge-based recommendation system (KB), Web data mining-based recommendation system (WDM)

The on top strategies are ready to use bound technology to record and analyse the client's browsing history, so as to urge the suggested result. However, they need their benefits and downsides severally. For instance, CB works by analysing the similarity of merchandise, it's visual affects however it's troublesome to search out new merchandise for clients; and CF works by analysing the similarity of clients, it will discover new merchandise for clients while not taking into consideration the characteristics of products, however throughout the terribly thin matrix that created by clients' analysis to products, the system's performance are going to be lower and lower. Therefore, several students use the mix of technology and even use technology in different areas.

Agent has the intelligence, initiative, and social and differentcharacteristics that the agent could also be on behalf of client's intention, action, interest, and so on. So as to create recommendation system to be a lot of nimble, intelligence, and may alter every quite recommendation technology's flaw, the students raises on the multi-Agent recommendation system [3].

Currently, the recommendation of multi-Agent System is not perfect: Resnick and Varian have given a definition for e-commerce recommendation system in the fonnal [4]: It is the use of e-commerce sites to provide customers with product information and recommendations to help customers decide which products would be bought, analog sales staff to help customers complete the purchase process. Literature [5] propose a multi-Agent Agent recommendation system and give a certain process of

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elaboration of the system simply, the insufficient is not giving the detailed analysis to each agent work flow; Literature [6] considered each Agent work flow, and has realized them simply, and researched on the muti-Agent recommendation system from the system's achievement; Based on multi-Agent system's research as well as above literature research, this article redesign Agent role, and detailed elaboration each Agent work flow and principle of work, research recommendation strategy Agent in emphatically and its recommendation technology [7].

The remainder of this paper is organized as in the following sections. We will describe the related works in Section 2. Section 3 will present the proposed e-commerce recommendation system based on anomaly detection information. In Section 4, we will analyse the proposed method and compare it with standard e-commerce recommendation methods. Finally, conclusion will be given in below Section .

II. PROPOSED WORK

In this paper, wetend to study a remarkable complication of recommending merchandise from e-commerce websites to clients behavioural changes or behaviour anomaly who don't have historical buy records, i.e., in "cold-start" case. We have a tendency to known as this complication cross-site cold-start product recommendation.

In our complication setting here, only the clients' anomaly data is offered and it's a difficult task to rework the social networking data into latent client option which could be effectively used for product recommendation. To handle this difficult task, we have a tendency to propose to use the connectedclients across e-commerce internet sites (client who have social networking accounts and have built purchases on e-commerce internet sites) as a bridge to map clients' social networking choices to latent choice for product recommendation. Figure 1 explains the architecture of the proposed system.

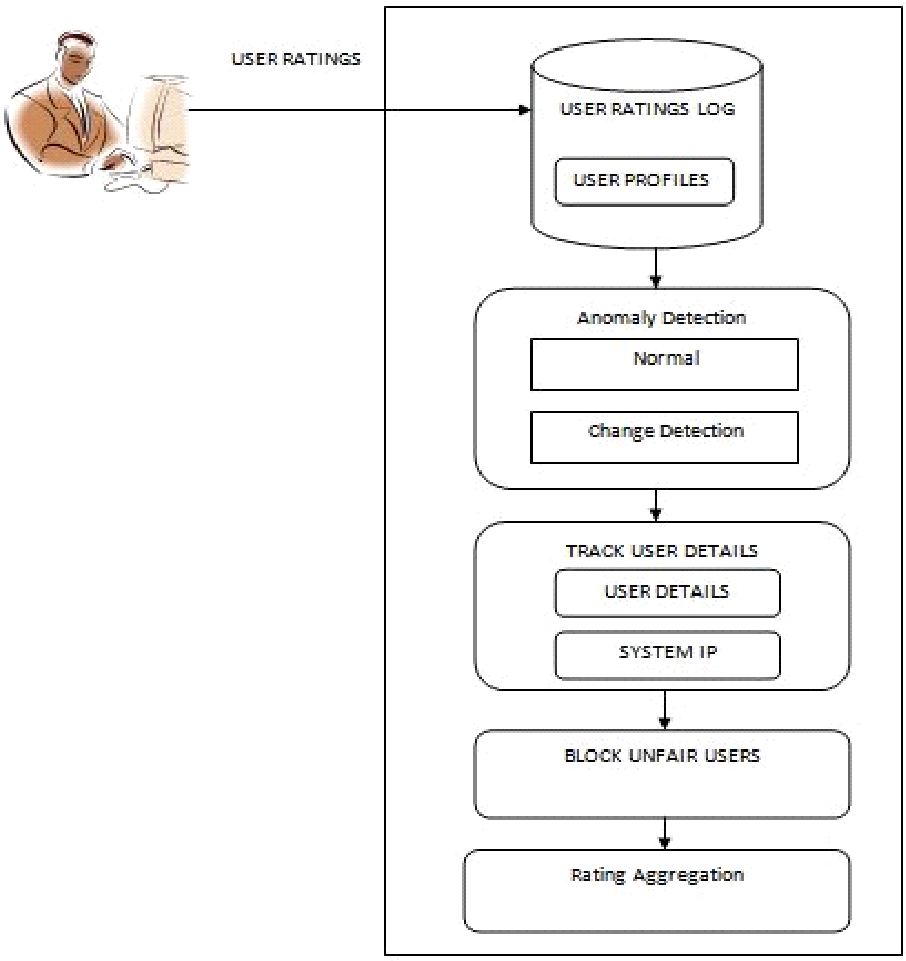

Figure 1. Proposed System Architecture

We then develop a feature-based matrix resolution approach which might leverage the learnt clientembedding's for cold start merchandise recommendation. In specific, we tend to propose anomaly detection for both client' and merchandises' feature representations (called client embedding's and merchandiseembedding's, respectively) from details collected from e-commerce internet sites exploitation perennial neural networks and so apply a changed gradient boosting trees technique to transform clients' behavioural features into clientembedding's. The following is the algorithm of proposed system.

Anomaly Detection algorithm

- **Training:**

Step 1: Select the number of options, n, for the entire system.
Step 2: Train with Username with multitudinous ratings for same merchandise.
Step 3: Train with IP address with multitudinous ratings for same merchandise.
Step 4: Perform feature choicespecific to every layer
Step 5: Introduce the trained models sequentially such solely the connections labelled as traditionalare passed to the next layer.

- **Testing:**

Step 6: Check the instance and label it either as censure or traditional.
Step 7: If the instance is labelled as censure, block it and pinpoint it as a censure delineate by the layer name at that it's spot. Else pass the sequence to the successive layer.
Step 8: Block the client for more unfair ratings

A. Collaborative filtering

Collaborative Filtering (CF) could be a unremarkably used technique in recommendation systems. It will status items of interest to a target client from an oversized choice of accessible items. It is split into 2 broad classes: memory-based algorithms and model-based algorithms. The latter needs it slow to create a model however recommends on-line articles quickly, whereas the previous is time-eating however does not need pre-building time. The Collaborative Filtering (CF) approach is maybe the foremost acquainted, most generally implemented, and most matures of the recommendation proposal. Its core idea is to utilize a collective intelligence to collect answers from crowd behaviour and details. A classification of CF algorithms that split them into 3 broad classes: memory-based algorithms and model-based algorithms.

With all the fundamental feature of On-line Social Networking System modules is build up within the initial module, to prove and value our system attributes. Given an e-commerce internet site, with a set of its clients, a set of products and purchase record matrix, each entry of which is a binary value indicating whether has purchased product. Each client is associated with a set of purchased products with the purchase timestamps. Furthermore, a small subset of clients can be linked to their accounts (or other social network accounts).

B. Calculating initialized probabilities

In this module, we tend to use the known possibility and collaborative filtering to estimatethe "initialized" possibility, by summation of several combinations and breaking those possibilities down into notable chances. It utilizes the feature public exhibition pairs of all the linked clients as coaching information. So as to prefigure a rating for a particular item for an energeticclient, we need to seek out all weights between the energeticclient and all other clients. Wethen tend to take all non-zero weights and have one another client "vote" on what they think the energeticclient ought to rate the item. Those with higher weights can matter a lot of within the voting method.

Once these votes square measure tallied, we've got a foreseen vote. Note that the voting relies on however faraway from a client's average they rate a picture show - that is, we wish to mention how far off from the energeticclient's average the energeticclient will rate the item. Thus, with a correlation, the energeticclient agrees with however far off the other client voted on a specific item; and with an negative correlation statistics, the energeticclient disagrees (i.e. goes within the opposite direction) from the other client's vote.

A demographic profile (often shortened as "a demographic") of a client like age, interest, sex and education are often employed by ecommerce companies to provide the best personalized services. We tend to extract clients' demographic characteristics from their general profiles. Demographic attributes are shown to be very significant in marketing, particularly in product adoption for customers.

C. Similarity measure

In order to live similarity, we wish to seek out the correlation between 2clients. This provides a value from -1 to one that determines who identical 2clients are. A value of one implies that they each rate within the precisely the identical manner, whereas value of -1 implies that they rate things specifically contrast (i.e. 1 high, another is low or vice versa). There is a tendency of 2 similarity measurements we used. The primary was the Pearson correlation coefficient. It is the fundamental correlation algorithm for samples tailored for rating details. It tries to live how what proportion 2clients vary along from their traditional vote's i.e., the direction/magnitude of every pick out collation to their balloting average. If they vary within the same means on the items they evaluated in common, they'll get a positive correlation or other way, they'll get a negative correlation.

Another similarity measuring is called vector similarity. We are able to 2 two clients as vectors in *n* dimensional house, wherever*n* is the no of items in a database. Like any 2 vectors, we are able tocompare the angle in the middle them. If the 2 vectors typically point within the same direction, they gain positive similarity; if they point in contrast directions, they gain negative similarity. To simulate this we tend to simply take the circular function the angle between these 2 vectors, which provides us a value from -1 to one.

Given a collection of symbol succession, a fixed-length vector illustration for every symbol are often learned in an latent space by put to use the context details among symbols, within which "similar" symbols are mapped to near positions. If we tend to treat each product ID as a word token, and turn the historical purchase records of a client into a time sealed sequence, we are able to use the constant strategies to learn product embedding's. In contrast matrix factorization, the order of historical purchases from a client are often naturally captured.

D. Product Recommendation

We exploited a local host based mostly on e-commerce dataset that contains some client group action records. Every group action record consists of a client's ID, a product ID and therefore the purchase timestamp. We tend to 1st cluster group action records by client IDs so acquire an inventory of purchased merchandise for everyclient.

For our techniques, a very important element is the embedding models, which might be set to 2 straightforwardarchitectures, specifically CBOW and Skip-gram. We tend to by trial and error compare the results of our technique ColdE exploitation these 2 architectures, and notice that the performance of exploitation Skip-gram is slightly worse than that of exploitation CBOW.

Our projected framework is very effective in addressing the cross-site cold-start product recommendation downside. We tend believe that our study can have profound impact on each analysis and business communities. We tend to formulate a unique drawback of recommending merchandise from associate e-commerce internet site to social networking clients in "cold-start" conditions. To the simplest of our data, it has been seldom studied before. We tend to propose to apply the use neural networks for learning correlativefeature representations for eachclients and merchandise from detailscollected from an e-commerce internet site. We tend to propose a modified gradient boosting trees technique to remodelclients' behavioural modification or anomaly attributes to latent feature illustration which might be simply incorporated for merchandise recommendation. We tend to propose and instantiate a feature-based matrix factorization approach by incorporating client and product options for cold-start product recommendation

III. EXPERIMENTAL ANALYSIS

To evaluate the approach in different scenarios, we select two datasets of e-Commerce and micro blogging environments: Yelp dataset and movie lens. The MovieLens datasets with rich rating data are the ideal test pool for CF approaches [13]. After cleaning, there are 2112 clients and 4856 items associated with 551 descriptors. The rating sparsity is comparatively low (97.42%) such that averagely one client has rated about 166 items. Each content descriptor is associated with about 60.6 items in average.

Generally, for real recommender systems, the content dimension is usually "fixed" while the item dimension is "incremental". Take the Yelp.com (footnote) for instance, the taxonomies structure (for example, types of restaurant, types of cuisine, etc.) is not changed frequently and can be used to classify new-entered businesses. However, the population of clients and businesses are increasing every day. The Yelp dataset is used for evaluating our approach, in which, there is over 45k clients and 11k items, categorized to 570 descriptors. The rating sparsity is 99.96%, and averagely a client only rated 5 items. In contrast, the content information is rich, as for each descriptor there are about 74.4 relevant items.

The experiment results of the dataset are collected in Table I. As we know that the ratings of Yelp dataset is very sparse (99.96%), such that the standard CF only completes 50.5% predictions. Comparing the metric of coverage, the sparsity problem also ruin the results of content based approaches (Tree Sim, Semantic, Crisp), especially for Crisp, only 8.3% is predictable. Generally, Tree Sim, Semantic have higher coverage than CF, maybe because neighbourclients are more easily found resorting to their preference on content information (with lower dimension) than resorting to their ratings on items (with higher dimension).

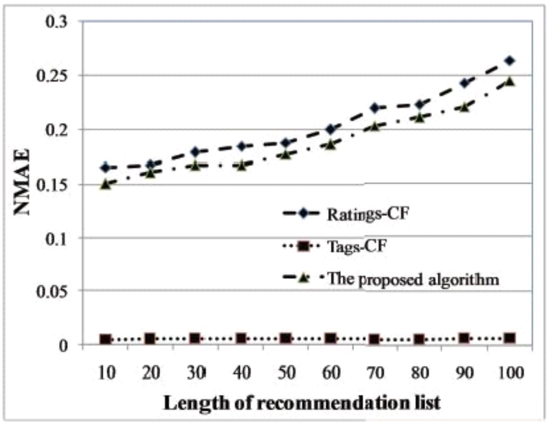

Figure 2. Precision for different length of recommendation list

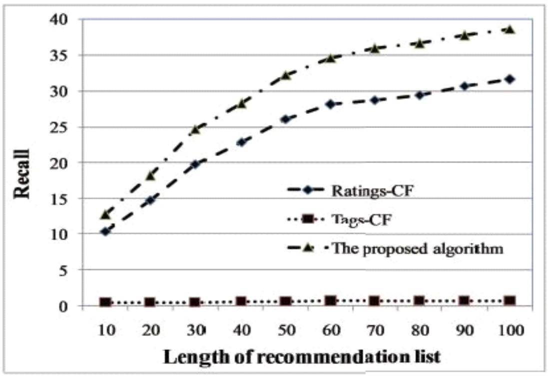

Figure 3. Recall for different length of recommendation list

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Comparing to these neighbourhood-based approaches, it performs the best result in terms of coverage: about 88.8% test data has been successful predicted. According to these comparisons, it can significantly alleviate the sparsity problem by directly matching client preferences and item content information in the sparse environment. In terms of ranking accuracy, represented by nDCG with p = 10 as default, CF (0.935), TreeSim (0.94) and Semantic (0.936) perform closely. The best performance is still achieved by FCM with 0.987. It indicates that though FCM does not generate crisp ratings it can rank the items accurately by using the fuzzy Topsis ranking method.

The ratings of Movie Lens is very dense, we can dilute the rating data to test the performance of each approach under different levels of sparsity. It should be mentioned that even after nine times of dilution, the sparsity of Movie lens (99.57%) is still lower than the sparsity of Yelp dataset (99.96%). First, Fig.5a demonstrates the trend of coverage of each approach with increasingly scarcity level. In overall, recommendation coverage is decreasing with the increase of rating sparsity. Particularly, for Crisp approach, the coverage decreases sharply 7 that only 12% at final. TreeSim and CF also reduce quickly when the data become sparse. Even at the last round, they can predict over 80%. In particular, for the sparsest test set (sparsity is 99.6%), only 12% is comparable (determined by the worst approach: Crisp) so that this test set is ignored for comparing nDCG as there are insufficient test data..

The proposed recommendation approach archives a better performance in terms of both recommendation coverage and accuracy compared to standard CF and the latest tree matching-based approach. Two variants of proposed approach are also evaluated as comparison and the results show the importance of social network and micro blogging data for the e-commerce recommendation system.

IV. CONCLUSION

Recommender systems are widely applied in e-commerce websites to help customers in finding the items they want. While the challenging research problems remain. However due to the consumer's individual differences and the context of the costumer tasks, different costumers are not possible to understand all the same. Meanwhile, the details sparsity reduces the accuracy of the recommendation system. In this paper, we research on E-Commerce recommendation and propose with collaborative preferences extension point of view. We use the preference feature construction. Then we make a collaborative preference. At last, we proposed a method for collaborative preferences extension based E-Commerce clustering recommendation. We measure the method in the large-scale anomaly detection information. It is used in each category of corpora, and the evaluation to each candidate word is acquired. Experiments and analysis are given to show that the proposed method is effective. The future work can attempt to enhance the potency with additional personalised recommendation system.

REFERENCES

[1] J. Wang and Y. Zhang, “Opportunity model for E-commerce recommendation: Right product; right time,” in Proc. 36th International. ACM SIGIR Conference Research Development Information Retrieval, 14/10/2013, pp. 303–312.

[2] Michael Giering, “Retail sales prediction and item recommendations victimisation customer demographics at store level,” SIGKDD ExplorationsNewsletter, vol. 10, no. 2, pp. 84-89, Dec. 2008.

[3] G. Linden, Brent Smith, and Jeremy York, “Amazon.com recommendations: Item-to-item collaborative filtering,” IEEE web Computing, vol. 7, no. 1, pp. 76–80, Feb. 2003.

[4] Valarie A. Zeithaml, “The new demographics and market fragmentation,” Journal of Mark., vol. 49, pp. 64–75, Summer. 1985.

[5] W. Xin Zhao, Y. Guo, Y. He, H. Jiang, Y. Wu, and X. Li, “We know what you would like to buy: A demographic-based system for product recommendation on microblogs,” in Proc. twentiethACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, Oct. 7, 2014, pp. 1935–1944.

[6] J. Wang, W. Xin Zhao, Y. He, and X. Li, “Leveraging product adopter information from on-line reviews for product recommendation,” in Proc. 9th Int. AAAI Conference Web Social Media, April, 2015, pp. 464–472.

[7] Y. Seroussi, F. Bohnert, and I. Zukerman, “Personalised rating prediction for new clients using latent factor models,” in Proc. 22nd ACM Conference Hypertext Hypermedia, 2011, pp. 47–56.

[8] Tomas. Mikolov, I. Sutskever, K. Chen, Greg Corrado, and J. Dean, “Distributed representations of words and phrases and their compositionality,” in Proc. Adv. Neural Inf. Process. Sys. Dec. 2013, pp. 3111–3119.

[9] Quoc. Le and T. Mikolov, “Distributed representations of sentences and documents,” CoRR, vol. abs/1405.4053, 2014.

[10] J. Lin, K. Sugiyama, M. Kan, and T. Chua, “Addressing cold-start in app recommendation: Latent client models constructed from twitter followers,” in Proc. 36th Annu. Int. ACM SIGIR Conference Research Development Information Retrieval, Aug 2013, pp. 283–292.

[11] T. Mikolov, K. Chen, G. Corrado, and J. Dean, “Efficient estimation of word representations in vector space,” CoRR, vol. abs/ 1301.378, 2013.

ISSN No: - 2456- 2165

[12] Y. Koren, R. Bell, and Chris Volinsky, “Matrix factorization techniques for recommender systems,” Computer society, vol. 42, no. 8, pp. 30– 37, Aug. 2009.

[13] Jerome H. Friedman, “Greedy function approximation: A gradient boosting machine,” Ann. Statist., vol. 29, pp. 1189–1232, 2001.

[14] Steffen R., “Factorization machines with libFM,” ACM Transaction on Intell. Syst. Technol., vol. 3, no. 3, May 2012.

[15] Ke Zhou, S. Hong Yang, and H. Zha, “Functional matrix factorizations for Cold-start recommendation,” in Proc. 34th Int. ACM SIGIR Conf. Res. Develop. Inf. Retrieval, July 2011, pp. 315–324.

[16] T. Chen, Hang Li, Q. Yang, and Yong Yu, “General functional matrix factorization using gradient boosting,” in Proc. Int. Conf. Machine Learn., USA, 2013, pp. 436–444.

[17] T. Chen, Weinan Zhang, Q. Lu, K. Chen, Z. Zheng, and Yong Yu, “SVDFeature: A toolkit for feature-based collaborative filtering,” J. Mach. Learn. Res., vol. 13, pp. 3619–3622, 2012.

[18] S. Rendle, Steffen, “Social network and Click-through prediction with factorization machines,” in Proc. KDDCup Workshop, Aug 2012.