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Item Recommendation for Word-of-Mouth Scenario in Social E-Commerce

Mrs.E. Lakshmi Prasanna[1] K Mounika[2], Biman Vignesh[2], Juveriya Rasheed[2],Sunkari Meenakshi[2]
[1.]Asst.Professor,Computer Science and Engineering, CMR Engineering College, medchal, T.S, India[2]B. Tech, Computer Science and Engineering, CMR Engineering College,medchal, T.S,India

Abstract: By allowing users to share things with their friends, social commerce, which differs from conventional e-commerce in which consumers buy products based on their own initiative searching or platform suggestions, turns a social network into an inclusive environment to conduct business. A user (sharer) may send a link to a product to friends with whom they are linked on social media. The sharer might gain commission from the site after the recipient buys the goods. The platform may help sharers drive sales by offering product options that are more likely to be bought during social sharing. To the best of our knowledge, this job of producing sharing ideas is brand-new and has never been investigated. We characterise it as item recommendation for word-of-mouth scenario. In this research, we offer a TriM (short for Triad-based word-of-mouth recommendation) model that can simultaneously capture the sharer's impact and the receiver's interest, two key elements that affect the receiver's decision to purchase the product. Our suggested TriM-Joint further enhances recommendation performance by using joint learning on two portions of interaction data to overcome the data sparsity problem. We demonstrate via trials that our suggested models outperform state-of-the-art models, with improvements of at least 7.4% and 14.4%, respectively.

1. INTRODUCTION

One of the hottest subjects nowadays is social commerce, which is a subset of e-commerce that includes social media. In social commerce, users are incentivized by the platform to spread the word about the various products it sells on social media by receiving financial rewards. This is the main distinction between conventional e-commerce platforms like Amazon1 and Taobao2, where consumers make purchases on their own initiative or based on the platform's passive endorsement. In other words, this strategy uses users' social networks to establish a new channel of advertising [1]. More precisely, a user may simultaneously act as both a consumer and an advertising. In other words, in addition to making purchases, the sharer also distributes goods to friends who act as recipients, earning incentives after the transaction is complete. A sharer, a receiver, and an item are the three roles that interact in this kind of product-sharing situation. Social commerce platforms like Beidian3 and Yunji4 are growing quickly under this new business model [2]. On such a platform, the phenomena of word-of-mouth [3], or the dissemination of knowledge from one person to another, is quite prevalent. Since people tend to trust what their friends recommend, a Nielsen study [4] found that 92% of consumers believe recommendations from friends and family play a more important role than advertisements. Using this occurrence as a foundation,[5] word-of-mouth marketing seeks to propose items to customers via these sharing activities rather than through direct advertising. As a result, it is crucial and necessary to rigorously analyse and simulate user behaviours of word-of-mouth marketing.

A Description Of The Project: In this essay, we look at the Word-of-Mouth (WoM) Recommendation Issue. On the social commerce platform, given a sharer and a receiver, we are asked to offer sharing suggestions (product candidates) that the receiver would be more likely to prefer. This sharer-item-receiver ternary link cannot be modelled by conventional recommendation algorithms, which only take into account user-item binary interactions. Social recommendation is the job that is most associated [6]. However, rather than relying on particular sharing behaviours, these social recommendation methods only take into account social connections between users. They are thus inappropriate for solving our situation. Compared to all other social recommendation studies, WoM recommendation really aims to investigate how social influence influences user decision-making at a more granular level.

2. LITERATURE SURVEY

2.1 Existing System

The following three issues face the brand-new yet crucial problem of word-of-mouth recommendations: Modelling of Ternary RelationshipsWord-of-mouth, recommendations are based on ternary relations made up of the sharer, item, and receiver as opposed to classic recommendation problems, which only consider user-item binary relations. Therefore, it is difficult to apply current strategies to this brand-new research issue[7]. The first problem we need to solve is how to describe the ternary relation and then use it to construct a recommender system.

• Complexity of User Behaviours: User behaviours are more intricate and complex in this ternary interaction. On the one hand, while engaging with goods, receivers display their own interests. However, sharers may have item-relevant influence over receivers, which may alter the receivers' behaviour. It may be quite difficult to figure out how to take these complex elements into account[8].

• Problem with Data Sparsity: Data sparsity is the subject of the last challenge. Data on sharing behaviours in real-world word-of-mouth recommendation settings is often difficult to come by and relatively limited. Additionally, because ternary relations are more complex than traditional recommendation tasks, it needs more training data. Therefore, it is challenging and worthwhile to research how to create an efficient model based on such sparse data.

2.2Proposed System

We begin by using multirelation learning in a knowledge graph to view the sharer, item, and receiver as head node, relation, and tail node, respectively, in order to overcome the aforementioned three problems. Then, to model the ternary relation and combine the two factors into our model for capturing the complexity of user behaviours, we propose a novel method called TriM (short for Triad based word-of-mouth recommendation).

We use user item binary interaction data from conventional e-commerce platforms to better capture receivers' preferences in order to address the data sparsity issue, and we propose a joint learning approach called TriM-joint by carrying out a cooptimization work. Here is a list of our main contributions[9].

• As far as we are aware, this is the first examination of the WoM recommendation issue from the standpoint of developing machine learning algorithms. We provide an in-depth investigation of social recommendation by examining the effect from sharers and interest of receivers in such a ternary interaction.

• By combining the components of both sharers and receivers, we present a unique model to learn the ternary connection. Joint learning is then used to help capture receivers' interests and address the data sparsity issue[10].

2.2 Method

Interests of Receivers ModellingWe use matrix factorization (MF) to simulate the receiver-item interactions in order to discover receiver preferences.Let X_{uri} stand in for the receiver $u_{r'}^{s}$ desire for item i, and let T, R, and Rn stand for the latent receiver and 8, respectively. Due to differing figure settings, there is a tiny discrepancy between the two numbers for Value+ in this instance.column vectors Tur and Ri representing the d-dimensional latent feature vectors of receiver u^r and item i, respectively, in the item feature matrices. The probability function of latent parameters is defined as follows, following a typical configuration for MF models[11]:

$$p(X|T,R,\sigma_X^2) = \prod_{u^r=1}^{m} \prod_{i=1}^{n} [N(X_{u^r i}|S(T_{u^r}^{T} R_i), \sigma_X^2)]^{I_{u^r i}^{X}}, \quad (1)$$

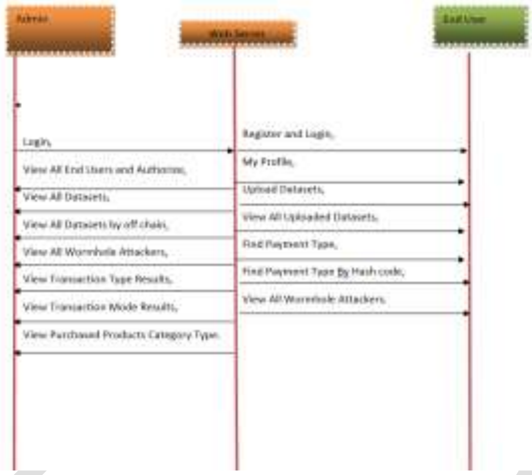

Fig 1: System Flow

3. SYSTEM ANALYSIS&DESIGN

3.1 TriM

Based on the aforementioned derivation, the observed preference X_{uri} is understood by the latent feature vectors of receiver u^r and item i, while the observed interaction Y_{usi} is realised as the influence of sharer us on item i given the interaction matrix of sharers and items. The preference as well as the impact should therefore be taken into account given the ternary relationship of the sharer us, item i, and receiver u^r. When interacting with an item shared by a friend, a user may be influenced by her friend in addition to her own preferences. Therefore, every observed interaction of the sharer, item, and receiver should take into account both of these two factors in order to define the model more realistically. In light of

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this, we model the conditional distribution across the measured ratings in the manner shown below.

$$\begin{aligned} & p(H,R,T|X,Y,\sigma_Z^2,\sigma^2) \\ & = \prod_{u^s=1}^{l}\prod_{i=1}^{n}\prod_{u^r=1}^{m}[N(Z_{u^s i u^r}|S(\alpha H_{u^s}^{\top}R_i \\ & +(1-\alpha)T_{u^r}^{\top}R_i),\sigma_Z^2)]^{I^Z_{u^s i u^r}} \times \prod_{u^s=1}^{l}N(H_{u^s}|0,\sigma^2 I) \\ & \times \prod_{i=1}^{n}N(R_i|0,\sigma^2 I) \times \prod_{u^r=1}^{m}N(T_{u^r}|0,\sigma^2 I), \end{aligned} \tag{2}$$

3.2 TriM-joint

One of the main problems with recommender systems is data sparsity. In general, adding characteristics data or other behavioural data may aid in enhancing the performance of recommendations. As a result, we may leverage the interaction data from the conventional e-commerce platform to solve our issue [12]. We can exchange the latent feature vectors of these users and objects since there are people and stuff that are shared across the two platforms. To represent the user-item activity on the conventional e-commerce platform more explicitly, we use matrix factorization in the manner shown below.

$$f_{MF}(u,i') = {R'}_{i'}^{\top} T'_u, \tag{3}$$

3.3 System Architecture:

Method of Optimisation of Our Proposed TriM

The parameters for our suggested TriM can be optimised using stochastic gradient descent (SGD) and mini-batch training.The following is a list of the gradients for updating parameters:

$$
\begin{aligned}
\frac{\partial \mathcal{L}_s}{\partial H_{u^s}} &= \sum_{(u^s,i,j,u^r)\in D_s} -S(-x(u^s,i,j,u^r)) \\
&\quad \cdot \alpha(R_i - R_j) + \beta\lambda H_{u^s}, \\
\frac{\partial \mathcal{L}_s}{\partial R_i} &= \sum_{(u^s,i,j,u^r)\in D_s} -S(-x(u^s,i,j,u^r)) \\
&\quad \cdot (\alpha H_{u^s} + (1-\alpha)T_{u^r}) \\
&\quad + \sum_{(u^s,j,i,u^r)\in D_s} S(-x(u^s,j,i,u^r)) \\
&\quad \cdot (\alpha H_{u^s} + (1-\alpha)T_{u^r}) + \lambda R_i, \\
\frac{\partial \mathcal{L}_s}{\partial T_{u^r}} &= \sum_{(u^s,i,j,u^r)\in D_s} -S(-x(u^s,i,j,u^r)) \\
&\quad \cdot (1-\alpha)(R_i - R_j) + \lambda T_{u^r}, \\
\frac{\partial \mathcal{L}_t}{\partial R_{i'}} &= \sum_{(u,i',j')\in D_t} -S(-y(u,i',j')) \cdot T_u \\
&\quad + \sum_{(u,j',i')\in D_t} S(-y(u,j',i')) \cdot T_u + \lambda R_{i'}, \\
\frac{\partial \mathcal{L}_t}{\partial T_u} &= \sum_{(u,i',j')\in D_t} -S(-y(u,i',j')) \\
&\quad \cdot (R_{i'} - R_{j'}) + \lambda T_u,
\end{aligned}
$$

where the sigmoid function S() and the indicator function I() are both used. We used a mini-batch gradient descent technique to learn the parameters in order to decrease the temporal complexity of model training. With sampling, the cost of the gradient update grows linearly in the number of sampled entries rather than the number of sharers, items, or receivers[13].

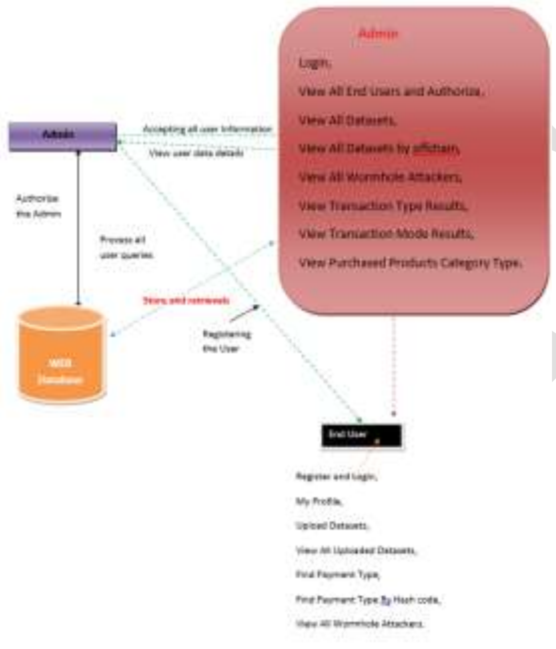

Fig 2 : System Architecture

3.4 Data Flow Diagram : Whenever a new system is developed, user training is required to educate them about the working of the system so that it can be put to efficient use by those for whom the system has been primarily designed[14]. For this purpose, the normal working of the project was demonstrated to the prospective users. Its working is easily understandable and since the expected users are people who have good knowledge of computers, the use of this system is very easy.

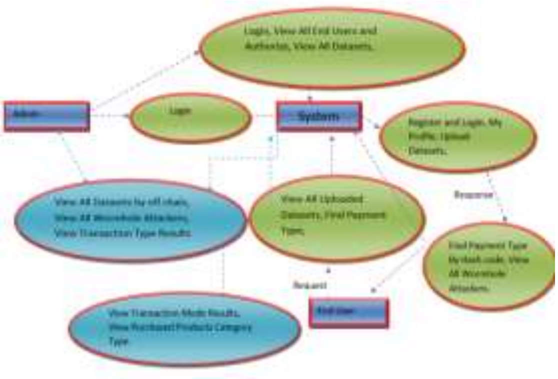

Fig 3: Data Flow Diagram

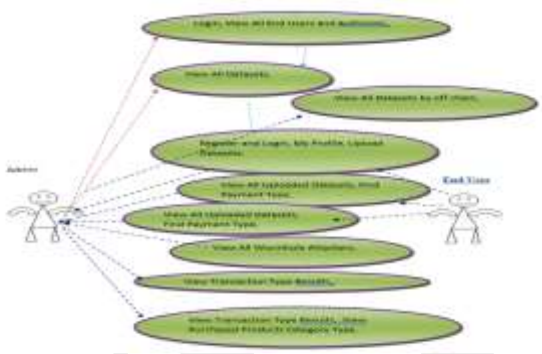

Fig 4 Use Case UML Diagrams

4. CONCLUSION

To the best of our knowledge, the subject of word-of-mouth promotion via social media has seldom been explored. via this paper, we extensively researched this issue. We put forward the innovative model TriM, which successfully models the sharer-item-receiver ternary relation and simultaneously captures the impact of the sharers and the interests of the receivers. We performed extensive tests on real-world datasets to assess our proposed model, and the results clearly demonstrate that TriM performs noticeably better than the current state-of-the-art approaches. The fact that we only use one private dataset for assessment is a limitation of our study[15]. We are aware of no additional publicly accessible data that would be appropriate for the WoM suggestion.

5. FUTURE SCOPE

We will do an online A/B test to better assess our model for future development. We may distribute our dataset following article acceptance and assist the community, particularly academics working on social recommendation. WoM is an in-depth study of social recommendation utilising this dataset.

6. REFERENCES

[1] Z. Huang and M. Benyoucef, "From e-commerce to social commerce: A close look at design features," Electronic Commerce Research and Applications, vol. 12, no. 4, pp. 246–259, 2013.

[2] Reuters, "Beidian debuted in times square and the rise of social e-commerce inchina," https://www.reuters.com/brandfeatures/venturecapital/article?id=34917, 2018.

[3] Manoj Kumar Singh and Rajesh Tiwari, " A Survey on Scheduling of Parallel Programs in Heterogeneous System", International Journal of Advanced Research in Computer Engineering & Technology, Vol. 1, Issue 8, October 2012, pp 357 - 360, ISSN: 2278 - 1323.

[4] Nielsen, "Consumer trust in online, social and mobile advertising grows," http://www.nielsen.com/us/en/insights/news/2012/consumertrust-in-online-social-and-mobile-advertising-grows.html, 2012.

[5] J. Tang, X. Hu, and H. Liu, "Social recommendation: a review," Social Network Analysis and Mining (SNAM), vol. 3, no. 4, pp. 1113– 1133, 2013.

[6] L. Guo, J. Ma, H.-R. Jiang, Z.-M. Chen, and C.-M. Xing, "Social trust aware item recommendation for implicit feedback," Journal of Computer Science and Technology, vol. 30, no. 5, pp. 1039–1053, 2015.

[7] Santosh Kumar Srivastava1a,, Yogesh Kumar Sharma2, Sheo Kumar3, "Characteristics Categorization Dataset KDD cup'99 ", Advances in Basic Science (ICABS 2019)
AIP Conf. Proc. 2142, 110034-1–110034-7; https://doi.org/10.1063/1.5122494.

[8] Santosh Kumar Srivastava Dr. Yogesh Kumar Sharma Dr. Yogesh Kumar SharmaSheo Kumar, " Precision enhancement of Intrusion detection system through outlier detection and feature classification",
International Journal of Control and AutomationVol. 12, No. 6, (2019), pp. 820-830, ISSN: 2005-4297 IJCA.

[9] L. Du, X. Li, and Y.-D. Shen, "User graph regularized pairwise matrix factorization for item recommendation," in International Conference on Advanced Data Mining and Applications (ADMA), 2011, pp. 372–385.

[10] Shikha Agrawal and Rajesh Tiwari, "Enhancing and Performance Comparison of various Truth Discovery Approach", International Journal of Technology, Vol. 1, Issue 2, July – December 2011, pp 76–86, ISSN(online): 2231- 3915 ISSN(print): 2231- 3907.

[11] Srihari Rao Nidamanuru, Rajesh Tiwari, Bhaskar Koriginja, Jincy Denny, J Ramesh Babu, "Identifying the Websites that Maintain Operational Standards through Obligation

Links to Website-Standards Approval Body", Turkish Journal of Computer and Mathematics Education, Vol. 12, Issue 10, 2021, pp 4456-4461, e-ISSN: 1309-4653.

[12] S. Rendle, C. Freudenthaler, Z. Gantner, and L. Schmidt-Thieme, "Bpr: Bayesian personalized ranking from implicit feedback," in The Conference on Uncertainty in Artificial Intelligence (UAI), 2009, pp. 452–461.

[13]. Predicting and Analyzing the E-commerce Customers Behaviour Using Advanced Frequent Pattern Mining in Machine Learning,Vol 5(1),Jan-Jun 2021 ISSN:2581-723X.

[14] Dr. C.N. RAVi , D. Palanivel Rajan, Desa Uma Vishweshwar, Edem Sureshbabu (CMREC)'A Review on Various Cloud-Based Electronic Health Record Maintenance System for COVID-19 Patients'Name of the Journal with ISSN:*Advances in Cognitive Science and Communications*, Cognitive Science and Technology - Springer Nature Singapore Pte Ltd. 2023 (CMREC Conference- ICCCE-2022)Vol. / Issue /PP. No. / Date/Month & Year of Publication:Impact Factor: https://doi.org/10.1007/978-981-19-8086-2_15, April 2023.

[15] Mrs.G.Sumalatha1 , Y.Jaideep Naidu M.Srividya, Karra karthik Reddy , D.Niharika, 'Smart OCR for Document Digitization', JASC: Journal of Applied Science and Computations, ISSN NO: 1076-5131, Volume VIII, Issue III, Macrh/2021.