e-ISSN:2582-7219

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY RESEARCH IN SCIENCE, ENGINEERING AND TECHNOLOGY

Volume 7, Issue 13, April 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 7.521

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

| ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 7.521| | Monthly Peer Reviewed & Refereed Journal |

|| Volume 7, Issue 13, April 2024 ||

International Conference on Intelligent Computing & Information Technology (ICIT-24)

Organized by

Erode Sengunthar Engineering College, Erode, Tamilnadu, India

A Comprehensive Survey of E-Commerce Recommendation Systems - Advancements and Challenges

V. Geetha[1], C. Sree Vyshnavi[2], Jitesh Kumar Sahoo[3], Pavan Krishna Malasani[4], Sabarinathan M[5]

Department of Information Technology Puducherry Technological University, Puducherry, India[1,2,3,4,5]

ABSTRACT: The core of any e-commerce site is an efficient Rec- ommendation System (RS) that can personalize user experience leading to improved click through rate and buyer satisfaction. This survey paper explores recent research in E-Commerce RS by examining their motivations and advancements in the field. Beginning with an overview of the related work, the study high- lights recent trends in ecommerce RS. The study considers major research articles published in reputed journals between 2020 and 2024. The RS used in ecommerce are classified into 6 types for the purpose of the survey – Content Based Filtering, Collaborative Filtering, Knowledge-Based Recommendation Systems, Context- Aware Recommendation Systems, Hybrid Recommendation Sys- tems, Large Language Model (LLM) Based Recommendation Systems. It notes the increasing popularity of Large Language Models as RS in few shot scenarios. Lastly, it suggests potential future research directions, offering insights into the evolving landscape of RS.

KEYWORDS: Collaborative Filtering, Content Based Filtering, Context Aware Recommendation Systems (CARS), E-commerce Recommendation Systems, Few shot learning, Knowledge Based Recommendation Systems, Large Language Models

I. INTRODUCTION

E-commerce or electronic commerce is becoming increas- ingly popular over time due to flexibility, cost-effectiveness, faster delivery, convenience shopping and the wide variety of options it provides. It is also beneficial for the organizations due to low cost of setting up and maintenance, increased revenue and ability to reach a wider customer base. However, unlike brick-and-mortar stores, understanding customers' pref- erences and providing best service is more challenging and dif- ficult in e-commerce systems. There are many challenges like searching through multi-modal data based on the text query, providing best recommendations for browsing and discovering products, ranking the products in stock to optimize the value

to all the stakeholders, Human Computer Interaction (HCI) etc [5].
Recommendation Systems (RS) are a key component of any e-commerce site. Due to the large number of options available on e-commerce sites, finding the best products that the user might be willing to buy is a challenging task. Over the years, due to the growth of e-commerce, there has also been an increasing amount of research in how the recommendations can be made better and more personalized. The aim is to improve customer satisfaction, while increasing the revenue for the company.

The current study focuses on the recent advancements in RS and the persistent challenges that need to be addressed. We start by providing an overview of some significant review articles in the domain. We then provide a detailed account of different types of RS and the recent advancements made in each type of RS.

II. RELATED WORK

E-commerce recommendation systems is an active area of research and numerous surveys have been made on the approaches used for recommendations. This section aims to provide an overview of some of the recent surveys in the area.

P. Malekpour Alamdari et al [1] in their review paper titled "Systematic Study on the RSs in the E-Commerce" studied selected papers from 2008 to 2019 and performed a Systematic Literature Review (SLR) of the research done in the field. They classified RS algorithms into 5 categories - Content-Based Filtering (CBF), Collaborative Filtering (CF), Demographic- Based Filtering (DBF), hybrid filtering, and Knowledge-Based Filtering (KBF). The authors performed a detailed comparative study of the methods used in each paper and identified the advantages and limitations of the methods. The paper also

lists out the open issues in the domain of e-commerce RS based on the selected papers. According to the SLR performed by the authors, Collaborative Filtering techniques were used more than the other 4 traditional methods. The selected tech- niques were compared based on metrics like accuracy, data source (implicit/explicit), operation cost, security, response time, scalability, diversity/novelty/serendipity and indepen- dence. According to the study, most of the research in the field focused on improving the accuracy of the recommendations, but other key metrics like security, serendipity, response time, novelty, diversity etc. are not considered in most studies. The study mainly focused on the 5 traditional mechanisms often used in e-commerce RS. However, it didn't consider other newly emerging techniques like deep learning, web mining algorithms and genetic algorithms.

K. C. Bodduluri et al [2] in their paper "Exploring the Land- scape of Hybrid Recommendation Systems in E-Commerce: A Systematic Literature Review," discusses various hybrid ap- proaches used for addressing the issues of cold start problem, data sparsity, and to better understand user needs that could not be effectively solved by single-architecture RS. The study focuses on the hybrid approaches proposed in 48 shortlisted studies in the past 6 years (2017-2023). The paper provides a detailed account of the challenges that most of the selected hybrid RS address and the combination of algorithms suitable to address the problems. According to the survey, 80% of RS that are built to counter major issues like cold start problem, and data sparsity use a hybrid of collaborative and content- based filtering as the base. The review observed a growing trend in the use of deep learning techniques for improving the performance of RS. The paper also provides an overview of various metrics used for evaluation of hybrid RS and the different datasets used for research in hybrid RS. According to the review, the MovieLens dataset[28] is the most commonly used dataset and nearly 40 out of selected 48 papers were based on user ratings.

A. De Biasio et al [3] in their research article titled "A systematic review of value-aware recommender systems," explore the economic value offered by the recommendations to the business. Value aware Recommendation Systems (VARS) focus on the value that the suggested items bring to the orga- nization rather than the alignment with user interest. VARS aim to optimize the value offered to various stakeholders including the customers, providers, as well as organization. The survey was performed using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines and 109 papers were considered for the review. The review classifies VARS into In-Processing and Post-Processing (re- ranking the recommendations based on their economic value) algorithms based on the time that the value is considered for recommendations. The paper also discusses the trade-off between accuracy and profitability of recommendations and the need to balance both.
Khoali, Mohamedey et al [4] in their review paper ti- tled "A Survey of One Class E-Commerce Recommendation System Techniques," provide a detailed account of one-class

recommendation approaches used in literature to address the challenges of data sparsity and absence of negative or neutral feedback. One-class recommendation is suitable in scenarios where only the implicit feedback is available. The paper lists out the common issues found in collaborative filtering and one- class RS and also proposes a neural network based Bayesian Personalized Ranking (BPR) technique for recommendations using implicit feedback. The proposed technique is tested on the MovieLens dataset [28] using AUC and MAE metrics and found to be reasonable.
The current study focuses on the literature from the past 4 years aiming to review the recent advancements in the field.

III. REVIEW OF SELECTED PAPERS

A. CLASSIFICATION OF RECOMMENDATION SYSTEMS

Recommendation systems in the e-commerce domain can be broadly classified into 2 types based on the type of problem they intend to solve – Prediction Problem and top k recommendation problem[3].
a) Prediction Problem: This involves predicting users' interest in an item. For example, in most cases, the rating a user might give to an item is predicted based on the product reviews. This can be modelled as a regression problem and is

commonly solved using algorithms like Logistic Regres- sion, XGBoost, and Random Forest [6]. Many authors have proposed advanced techniques to solve the rating prediction problem. P. Sitkrongwong et al [18] propose a Context-aware user and item representation based rating prediction.
b) Top k recommendation problem: TAs the name sug- gests, this involves providing top k items as recommendations to the users based on the items in the stock. A detailed account of various proposed techniques for providing top k recommendations is provided in the further sections.

Based on the methodology used to solve the recommenda- tion problem, RS can be classified as –
i. Content-Based Filtering: Recommend items similar to those a user has liked or interacted with in the past based on the content/features of the items.
ii. Collaborative Filtering: Recommend items based on the preferences of similar users or the similarity between items. It does not require explicit item features. It can be classified as Memory Based and Model Based Collaborative Filtering. A detailed overview of these techniques is provided in further sections.
iii. Knowledge-Based Recommendation Systems: Recom- mend items based on explicit knowledge representa- tions such as ontologies, knowledge graphs, or domain- specific rules.
iv. Context-Aware Recommendation Systems: Recommend items based on contextual factors such as time, location, or user behavior to provide more relevant recommenda- tions.
v. Hybrid Recommendation Systems: Combines multiple recommendation techniques (such as content-based, col- laborative filtering, or knowledge-based) to provide more accurate and diverse recommendations.
vi. Large Language Model (LLM) Based Recommenda- tion Systems: Utilizes large language models like GPT for generating recommendations, often leveraging the model’s understanding of natural language and vast textual data for personalized recommendations.

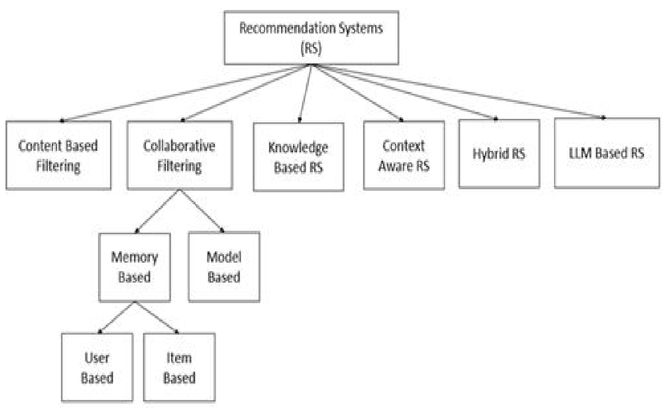

Fig. 1. Classification of Recommendation Systems

These classes are not mutually exclusive. Most of the proposed systems fall under more than one of these categories. Apart from these classes, many other classifications are made in recent literature [3] like Value Aware RS, Multi-objective RS, Multi-criteria RS, Multi-stakeholder RS, At-
tribute aware RS, Price aware RS etc.

B.CONTENT BASED FILTERING

Content Based Filtering is a recommendation method that relies on intrinsic characteristics of items (like the item fea- tures, description or metadata) and users. New items similar to the items the user has interacted with in the past are recommended in this method.
Saini, Kapil, and Ajmer Singh [8] propose a highly scalable RS using Content Based Filtering technique and attempt to solve the cold start problem in RS using self-supervised learn- ing. The authors propose a RS combining stacked Long Short- Term Memory (LSTM) and an attention based autoencoder. The proposed system was simulated using Amazon product review dataset. In this study, a 3 stage recommendation tech- nique is proposed. The first stage involves the deep learning model learning the important features from the dataset. The second stage involves knowledge transfer

followed by the third stage where the recommendation actually happens. The study proves that the proposed system is more accurate than existing TF-IDF based and Count Vectorizer based systems and can be used on large datasets.
R.J. Kuo and Hong-Ruei Cheng in their research article
[9] titled "A content-based recommender system with con- sideration of repeat purchase behavior," focus on the use of transactional dataset with product descriptions for recommen- dations. According to the authors, it is hard to predict user's dynamically changing preferences using binary (purchased/did not purchase) or subjective weighing methods to represent user's preferences. This study adds a new component for adjusting the user profile based on user feedback to the tradi- tional Content Based RS. This feedback adjuster component

considers customers' repeat purchase behaviour for customer implicit feedback.
A. Pujahari and D.S. Sisodia [10] propose the refinement of item features to deal with inconsistent and sparse features before content-based filtering. The study proposes a two- fold approach. The item features are refined using matrix factorization in the first step. The missing feature vectors are predicted using latent factor procedure. Using matrix factorization, the global information is obtained. This is useful to deal with sparsity in item features in the dataset. The user preference profiles are generated using an iterative learning approach where misclassified items are penalized. AdaBoost ensemble classifier is used to build user profiles. The iterative approach makes the model more robust and can make rating prediction for new items.

C.COLLABORATIVE FILTERING
Collaborative Filtering is a recommendation method that recommends personalized recommendations to a user based on the items similar users have interacted with. This is based on the assumption that users who have interacted with similar items in the past will have similar preferences.

Traditional collaborative filtering-based systems have the problems of sparsity and cold start problem. A. Fareed et al
[11] in their research article titled "A collaborative filtering recommendation framework utilizing social networks," pro- pose a modified version of User Based Collaborative Filtering technique that finds similar users based on a weighted combi- nation of 2 factors - their ratings and social connections. The weights for each factor are learned through an optimization process. The proposed framework is tested on a dataset of movie ratings and social connections among users. The so- cial connections among users can be used to know users' interests and preferences. This can help in generating more personalized recommendations. According to the study, the proposed system outperforms traditional collaborative filtering techniques in terms of recommendation accuracy, relevance and diversity of recommendations. The paper mentions that this proposed technique can potentially address sparsity and cold start challenges in collaborative filtering.

R. Rismala et al [13] propose a model-based multi-criteria collaborative filtering (MCCF) method. This uses the ratings given by users under various criteria of items. The authors attempt to address the challenge of building an aggregation function that is efficient, scalable as well as personalized by proposing a neural network based aggregation function in MCCF (P-FFNN-MCCF and P-DNN-MCCF). The traditional total based aggregation function, though efficient, lacks per- sonalization. This is enhanced considering dynamic personal information of the user based on rating history along with the multi-criteria ratings. The model has been evaluated on 4 real world datasets and has been found to be better than the baseline models considered in terms of ROC AUC and macro F1-score.

D.KNOWLEDGE BASED RECOMMENDATION SYSTEMS
Knowledge Based RS use structures like knowledge graph to represent the users, products, along with their attributes and relationships between them. Z. Shokrzadeh et al [15] propose a knowledge graph based recommendation system using knowledge graph embedding and neural collaborative filtering. The knowledge graph is constructed based on user- user, user-tag, user-source and tag-source relationships from Hetrec2011-Delicious-2k dataset using sophisticated knowl- edge graph embedding methods like ConvE, ComplEx and TransE to learn the necessary low-dimensional vector repre- sentations. The proposed technique addresses the challenges of cold-start, redundancy and ambiguity problems using multi- hop neighbours in the knowledge graph. Neural collaborative filtering is used for recommending products, tags and sources to users by applying matrix operations and fine tuning pre- trained embeddings generated using knowledge graph embed- ding.

| ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 7.521| | Monthly Peer Reviewed & Refereed Journal |

|| Volume 7, Issue 13, April 2024 ||

International Conference on Intelligent Computing & Information Technology (ICIT-24)

Organized by

Erode Sengunthar Engineering College, Erode, Tamilnadu, India

Y. He et al [16] proposed a knowledge graph based recom- mendation system using contrastive learning (CL). CL frame- work helps to deal with the challenge of data sparsity. The proposed Knowledge based Recommendation with Contrastive Learning (KRCL) framework addresses the shortcoming of existing CL methods that result in noise and irrelevant infor- mation during knowledge view generation. KRCL framework generates dual views from knowledge graph and user-item interaction graph based on data augmentation and knowledge graph information mining techniques. The study proposes a novel relation aware GNN model to encode the knowledge view that addresses the shortcoming of CL methods that don't consider the relations between edges and entities. A contrastive loss technique is designed to ensure the representations of the same item in various knowledge graph views are closer to each other. The proposed KRCL framework was evaluated using 3 datasets covering different domains – Yelp2018, Amazon- Book and MIND and found outperform the baseline models considered in all three datasets.

E.CONTEXT AWARE RECOMMENDATION SYTEMS

Context Aware Recommendation Systems (CARS) are sys- tems that consider the user's context in terms of their demo- graphics, time of purchase, environmental conditions in their location, and user activity.

P. Sitkrongwong et al [18] propose a novel unsupervised method to extract the context from reviews given by the users. In this paper, it is emphasized that user reviews can be used to solve the problem of sparse product ratings in e-commerce sites. The context is automatically extracted using a Context Aware Region Embedding (CARE) technique. The extracted context is used to build user and item representations based on different relevance levels instead of considering every word in the reviews. The proposed technique using interaction and attention modules is proved to outperform existing context- aware and review based recommendation methods for rating prediction by testing on three review datasets. The study claims that, the proposed method can be used for extraction of contexts from reviews in any recommendation domain as pre-defined contexts are not used.

Sequential RS can be considered as a sub class of CARS as they are based on the sequential actions (purchases or views or clicks) made by the user. U. Padungkiatwattana et al [19] propose an attention based model for sequential recommendation. The authors argue that global item represen- tations derived from considering all the items in the whole sequence without considering item-adjacency are not efficient in providing relevant recommendations. In this study, a novel attention based local-interaction (considering item-adjacency) model (ARERec) is proposed for sequential recommendation using region-embedding technique on user and item historical sequences. The study proposes the use of multi-head attention mechanism to personalize recommendations for each user based on user-specific information after applying neighbour based collaborative filtering. The authors claim that ARERec outperforms other sequential methods using Recurrent Neu- ral Networks (RNN) and attention such as GRU4REC [22], SASRec [23] and BERT4Rec [24] in terms of the hit rate and Normalized Discounted Cumulative Gain.

Transformers with self-attention are recently proven to be efficient in performing next basket recommendation task in e- commerce sites due to their generalizability and their ability to capture sequential information in user behaviour [20]. E. Frolov and I. Oseledets [21] attempt to develop a viable and light weight approach to achieve similar efficiency by mimicking self-attention mechanism in neural networks. The authors propose 2 new tensor factorization based models based on Hankel matrix representation with a shallow linear architecture. These models have been developed considering the SASRec model[20] as the base line for comparision. The authors proposed 2 models that act either on entire user sequence or within a fixed length context window. The 2nd model is found to provide better quality recommendations. Due to the shallow nature, it can be trained faster than the deep neural network based transformers and performs at par with neural network based models in terms of recommendation quality of top n recommendations.

F.LLM BASED RECOMMENDATION SYSTEMS

Large Language Model based RS is a new area of research. It has gained a lot of importance owing to the few short learning ability of LLMs [7]. Few shot learning is important as such scenarios pose a major challenge to explicit feedback- based RS. LLM based RS basically use the explicit feed- back from users for generating personalized recommendations. Z.Wang [12] considers the effectiveness of LLMs as few shot recommenders in different recommendation domains by conducting ablation experiments. The study devises a template for prompting LLMs to generate user and item representations based on explicit feedback. The author suggests that LLMs are effective for recommender systems due to their generative and logical reasoning capabilities. LLMs can perform well in various domains due to their adaptability thus aiding in generalizability. Based on the experiments, the study observes

| ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 7.521| | Monthly Peer Reviewed & Refereed Journal |

|| Volume 7, Issue 13, April 2024 ||

International Conference on Intelligent Computing & Information Technology (ICIT-24)

Organized by

Erode Sengunthar Engineering College, Erode, Tamilnadu, India

that, in contrast to conventional language models, ChatGPT can generate expansion context even when provided with limited information.

TABLE I
SUMMARY OF RECOMMENDATION SYSTEMS RESEARCH

Paper	**Datasets used**	**Techniques used**	**Advantages**	**Limitations**
Saini et al, 2024 [8]	Amazon product review dataset [27]	Content based RS com-bining stacked LSTM and an attention based autoencoder	Highly scalable, Ad-dresses cold start prob-lem	Does not consider the value offered to the stakeholders
R.J. Kuo and Hong-Ruei Cheng, 2022 [9]	An online retail dataset (trans-actional data)	A feedback adjuster component is introduced in traditional content based RS to regulate customer implicit feedback	Objective approach – avoids subjective judgements, Adapt to changing preferences using feedback adjuster	Considers only pur-chase data
A. Pujahari and D.S. Sisodia, 2022 [10]	MovieLens-1M [28], Last.fm, and Netflix	Matrix Factorization is used for item feature refinement. AdaBoost ensemble classifier used to build user profiles using an iterative approach	Deals with inconsistent and sparse features in the data efficiently	Does not consider scalability of the system
A. Fareed et al, 2023 [11]	MovieLens dataset [25], Book-Crossing dataset [17]	Uses matrix factoriza-tion for Collaborative Filtering. Network vi-sualization is used to analyze social network.	Outperforms traditional CF in recommendation accuracy, Helps miti-gate sparsity problem, Scalable	Generalizability is not considered.

R. Rismala et al, 2024 [13]	Trip Advisor [26], Yahoo! Movies (YM), and Beer Advocate (BA) datasets	Model based multi criteria collaborative filtering - neural network based aggregation function in MCCF (P-FFNN-MCCF and P- DNN-MCCF)	Aggregation functions are adjusted to user's personal characteristics – resulting in more accurate and personalized recommendations	Does not consider the partial preference problem in multi criteria ratings. Considers only accuracy - scalability and computational efficiency not considered
Z. Shokrzadeh et al, 2024 [15]	Hetrec2011-Delicious-2k dataset	ConvE, ComplEx and TransE for knowledge graph embedding. Neural Collaborative Filtering for recommending tags and sources(using basic matrix operations).	Addresses redundancy, ambiguity in recommendations. Provides a solution to cold start problem for new tags.	Sequential nature of the interactions is not considered. The knowledge graph proposed is not dynamic.
Y. He et al, 2023 [16]	Yelp2018 [29], Amazon-Book [27] and MIND	KRCL framework – uses data augmentation and knowledge graph (KG) information mining techniques for KG view generation. relation aware GNN model to	CL can deal with sparse data, Highly scalable, Performs better than traditional collaborative filtering techniques	Does not consider the sequential nature of the user-item interactions

| ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 7.521| | Monthly Peer Reviewed & Refereed Journal |

|| Volume 7, Issue 13, April 2024 ||

International Conference on Intelligent Computing & Information Technology (ICIT-24)

Organized by

Erode Sengunthar Engineering College, Erode, Tamilnadu, India

		encode the knowl- edge view		
P. Sitkrongwong et al , 2020 [18]	TripAdvisor [26], Amazon Software and Amazon Movies & TV [27]	Unsupervised method Context Aware Region Embedding (CARE) – to automatically extract context	Generalized – can be used in any recommen- dation domain to ex- tract context from text reviews	Only suitable for products with text reviews
U. Padungkiat- wattana et al, 2022 [19]	Movielens [28], Goodreads, Yelp [29]	Attention based local- interaction model (ARERec) (considering item- adjacency) for sequential recommendation. Multi-head attention mechanism for personalization based on user specific information	Outperforms state- of-the-art sequential methods using RNN and attention in terms of hit rate and Normalized Discounted Cumulative Gain	Does not consider scalability.
E. Frolov and I. Oseledets , 2023 [21]	Movielens – 1M [28], Amazon Beauty, Amazon Toys and Games, Steam [27]	Mimic self attention mechanism using Ten- sor Hankelization	Lightweight alternative with same quality rec- ommendations as neu- ral network based mod- els.	Cannot capture more intricate non- trivial dependencies
Z. Wang, 2024 [12]	Douban Chinese Moviedata- 10M [14]	Uses ChatGPT to generate textual user and item embeddings	Few shot learning ca- pability with explicit feedback	Does not consider implicit feedback. LLMs can be re-

		– these are used for interaction prediction and direct recommendation		source intensive.

IV. CONCLUSION

This study performed a comprehensive survey of the re- cent advancements in e-commerce recommendation systems. Significant advancements made in the field of Content Based Filtering, Collaborative Filtering, Knowledge-Based Recommendation Systems, Context-Aware Recommendation Systems are discussed in detail. Moreover, early research Large Language Model (LLM) Based Recommendation Systems is explored. It is observed that most of the research papers focus on improving the accuracy of recommendations. However, in order to improve user satisfaction as well as the value obtained by all the stakeholders of the system, more metrics like diversity, serendipity and novelty of recommendations also need to be considered.

REFERENCES

1. P. M. Alamdari, N. J. Navimipour, M. Hosseinzadeh, A. A. Safaei and A. Darwesh, ”A Systematic Study on the Recommender Systems in the E-Commerce,” in IEEE Access, vol. 8, pp. 115694-115716, 2020, doi: 10.1109/ACCESS.2020.3002803.
2. K. C. Bodduluri, F. Palma, A. Kurti, I. Jusufi and H. Lo¨wenadler, ”Exploring the Landscape of Hybrid Recommendation Systems in E- Commerce: A Systematic Literature Review,” in IEEE Access, vol. 12, pp. 28273-28296, 2024, doi: 10.1109/ACCESS.2024.3365828.
3. A. De Biasio, A. Montagna, F. Aiolli, and N. Navarin, “A system- atic review of value-aware recommender systems,” in Expert Sys- tems with Applications, vol. 226, Art. no. 120131, Sep. 2023, doi: 10.1016/j.eswa.2023.120131.
4. Mohamed Khoali, Yassin Laaziz, Abdelhak Tali, and Habeeb Salaudeen, ”A Survey of One Class E-Commerce Recommenda- tion System Techniques,” in Electronics, vol. 11, no. 6: 878, 2022, doi:10.3390/electronics11060878
5. Manos Tsagkias, Tracy Holloway King, Surya Kallumadi, Vanessa Murdock, and Maarten de Rijke, “Challenges and research opportunities in e-commerce search and recommendations,” in SIGIR Forum, vol. 54, 1, Article 2 (June 2020), 23 pages, doi: 10.1145/3451964.3451966
6. D. Vedananda, E. Skanda, Prasad, V. T., ”Survey on Forecasting of E-Commerce Product Rating,” in International Journal For Science Technology And Engineering, vol. 11, pp. 2140-2143, 2023, doi: 10.22214/ijraset.2023.49904
7. T. B. Brown, ”Language models are few-shot learners”, Proc. NIPS, pp. 1877-1901, 2020.
8. Kapil Saini and Ajmer Singh, ”A content-based recommender system using stacked LSTM and an attention-based autoencoder,” in Measure- ment: Sensors, vol. 31, 2024, p. 100975.
9. R.J. Kuo and Hong-Ruei Cheng, ”A content-based recommender system with consideration of repeat purchase behavior,” Applied Soft Comput- ing, vol. 127, pp. 109361, 2022. doi: 10.1016/j.asoc.2022.109361.
10. A. Pujahari and D.S. Sisodia, ”Item feature refinement using matrix factorization and boosted learning based user profile generation for content-based recommender systems,” Expert Systems with Applications, vol. 206, pp. 117849, 2022. doi: 10.1016/j.eswa.2022.117849.
11. A. Fareed, S. Hassan, S. B. Belhaouari, and Z. Halim, ”A collabo- rative filtering recommendation framework utilizing social networks,” Machine Learning with Applications, vol. 14, p. 100495, 2023, doi: 10.1016/j.mlwa.2023.100495
12. Z. Wang, ”Empowering Few-Shot Recommender Systems With Large Language Models-Enhanced Representations,” in IEEE Access, vol. 12, pp. 29144-29153, 2024, doi: 10.1109/ACCESS.2024.3368027.
13. R. Rismala, N. U. Maulidevi, and K. Surendro, ”Personalized neural network-based aggregation function in multi-criteria collaborative fil- tering,” Journal of King Saud University - Computer and Information Sciences, vol. 36, no. 1, p. 101922, 2024.

14. D.Liu,Y.Gao,andY.Xu.(2019).DoubanMoviedata.[Online].Available: http://moviedata.csuldw.com/ and https://github.com/csuldw/AntSpider
15. Z. Shokrzadeh, M.-R. Feizi-Derakhshi, M.-A. Balafar, and J. Bagherzadeh Mohasefi, "Knowledge graph-based recommendation sys- tem enhanced by neural collaborative filtering and knowledge graph embedding," Ain Shams Engineering Journal, vol. 15, no. 1, p. 102263, 2024.
16. Y. He, X. Zheng, R. Xu, and L. Tian, "Knowledge-based recommenda- tion with contrastive learning," High-Confidence Computing, vol. 3, no. 4, pp. 100151, 2023.
17. X. Qian, H. Feng, G. Zhao, and M. Tao, "Personalized recommenda- tion combining user interest and social circle," IEEE Transactions on Knowledge and Data Engineering, vol. 26, no. 7, pp. 1763-1777, 2018.
18. P. Sitkrongwong, A. Takasu and S. Maneeroj, "Context-Aware User and Item Representations Based on Unsupervised Context Extraction From Reviews," in IEEE Access, vol. 8, pp. 87094-87114, 2020, doi: 10.1109/ACCESS.2020.2993063.
19. U. Padungkiatwattana, T. Sae-Diae, S. Maneeroj and A. Takasu, "AR- ERec: Attentive Local Interaction Model for Sequential Recommenda- tion," in IEEE Access, vol. 10, pp. 31340-31358, 2022, doi: 10.1109/AC-CESS.2022.
20. W.-C. Kang and J. McAuley, "Self-attentive sequential recommenda- tion," in Proc. IEEE Int. Conf. Data Mining (ICDM), pp. 197-206, Nov. 2018.
21. E. Frolov and I. Oseledets, "Tensor-Based Sequential Learning via Hankel Matrix Representation for Next Item Recommendations," in IEEE Access, vol. 11, pp. 6357-6371, 2023, doi: 10.1109/AC- CESS.2023.3234863.
22. B. Hidasi, A. Karatzoglou, L. Baltrunas and D. Tikk, "Session-based recommendations with recurrent neural networks," arXiv:1511.06939, Nov. 2015.
23. W.-C. Kang and J. McAuley, "Self-attentive sequential recommenda- tion," arXiv:1808.09781, 2018.
24. F. Sun, J. Liu, J. Wu, C. Pei, X. Lin, W. Ou, et al., "BERT4Rec: Sequential recommendation with bidirectional encoder representations from transformer," arXiv:1904.06690, 2019.
25. P. Moradi and S. Ahmadian, "A reliability-based recommendation method to improve trust-aware recommender systems," Expert Systems with Applications, vol. 42, no. 21, pp. 7386-7398, 2015.
26. http://www.cs.cmu.edu/jiweil/html/hotel-review.html
27. https://nijianmo.github.io/amazon/index.html
28. https://grouplens.org/datasets/movielens/1m/
29. https://www.yelp.com/dataset