algorithms

MDPI

Editorial

Guest Editorial for the Special Issue "New Trends in Algorithms for Intelligent Recommendation Systems"

Edward Rolando Núñez-Valdez * and Vicente García-Díaz

Department of Computer Science, University of Oviedo, 33007 Oviedo, Asturias, Spain; garciavicente@uniovi.es
* Correspondence: nunezedward@uniovi.es

Currently, the problem of information overload, a term popularized by Alvin Toffler in his book *Future Shock* [1], is more present than ever due to the rapid development of the Internet. Because of the large number of electronic resources that are available on the Internet, it is becoming increasingly complex for users to select the most relevant and significant information. To solve the problem of information overload, various techniques, algorithms, and tools are currently used to classify or filter this huge amount of data, with the aim of analysing the users' behaviour, interests, or tastes [2].

A recommender system is a set of information retrieval techniques that, through advanced analysis of massive data, can select the most relevant and significant information for users in order to help them make intelligent decisions. These systems use different kinds of algorithms to help users quickly and easily discover the information that they need in a specific context through information filtering.

With the development and implementation of efficient algorithms for recommender systems, users can find different types of information, such as hotels or tourist places [3–6], movies [7–11], books [12–14], songs [15–17], websites [18–20], and any kind of information that may interest them. Among the most popular algorithms of these systems, we can highlight content-based systems, collaborative filtering, and hybrid recommender systems, among others. To make good predictions, these systems use the collective ratings from users of a set of data, which are obtained explicitly or implicitly [21].

As recommender systems have an increasingly central role in decision making in different scenarios, the need for researchers and developers to be able to refine and propose new models, algorithms to convert unstructured data into structured data, or algorithms to optimize the performance of these systems becomes more important, considering that these algorithms are usually adapted to the set of data that are available for a particular domain of knowledge.

This Special Issue on "New Trends in Algorithms for Intelligent Recommendation Systems" provides a platform to exchange new ideas by researchers and practitioners in the field of recommender systems and their applications in many areas. The research community has responded with enthusiasm. Only research articles that meet the journal's requirements were accepted for publication after peer review. We received sixteen articles for this Special Issue, and we finally included seven articles, which have been fairly peer-reviewed and accepted for publication. The following points highlight the remarkable scientific achievements of the accepted manuscripts.

Firstly, the paper entitled "Sparks of Artificial General Recommender (AGR): Experiments with ChatGPT" by Guo Lin and Yongfeng Zhang (Contribution [1]) investigates the feasibility of developing an Artificial General Recommender (AGR) using Large Language Models (LLMs). The idea is to engage in natural dialogues and generate recommendations across various domains. The authors also show the potential for ChatGPT to serve as an AGR, although several limitations and areas for improvement are also identified.

The paper entitled "A Survey of Sequential Pattern Based E-Commerce Recommendation Systems" by Christie I. Ezeife and Hemmi Karlapalepu (Contribution [2]) presents a

Citation: Núñez-Valdez, E.R.; García-Díaz, V. Guest Editorial for the Special Issue "New Trends in Algorithms for Intelligent Recommendation Systems". *Algorithms* **2024**, *17*, 255. https://doi.org/10.3390/a17060255

Received: 5 June 2024
Accepted: 6 June 2024
Published: 10 June 2024

review that focuses on the algorithms of existing E-commerce recommendation systems that are based on sequential patterns. It provides a comprehensive and comparative performance analysis of these systems, exposing their methodologies, achievements, limitations, and potential for solving more important problems in this domain.

The paper entitled "Addressing the Cold-Start Problem in Recommender Systems Based on Frequent Patterns" by Antiopi Panteli and Basilis Boutsinas (Contribution [3]) addresses the cold-start problem in recommender systems based on frequent patterns, which are highly frequent in one set of users, but less frequent or infrequent in other sets of users. The proposed methodology forms different clusters of old users and then discovers discriminant frequent patterns for each cluster, exploiting this to infer the purchase behaviour of new users.

The paper entitled "A Novel Hybrid Recommender System for the Tourism Domain" by Chalkiadakis et al. (Contribution [4]) proposes a novel hybrid recommender system for the tourism domain, combining a Bayesian preferences elicitation component, which operates by asking the user to rate generic images in order to build a user model, and a novel content-based (CB) recommendation component.

The paper entitled "An Efficient Approach to Manage Natural Noises in Recommender Systems" by Luo et al. (Contribution [5]) presents a new approach to managing natural noises in recommendation systems. The authors provide the detection criteria for natural noises based on the classifications of users and items. After the noises are detected, they correct them with threshold values that are weighted by probabilities. Their experimental results show that the proposed method can effectively correct natural noise and greatly improve the quality of recommendations.

The paper entitled "Using Graph Neural Networks for Social Recommendations" by Tallapally et al. (Contribution [6]) proposes the RelationalNet algorithm, which not only models user–item and user–user relationships but also item–item relationships using graphs. The paper then uses these as input to the recommendation process. The rationale for utilizing item–item interactions is to enrich the item embeddings by leveraging the similarities between items.

Finally, the paper entitled, "Information Retrieval and Machine Learning Methods for Academic Expert Finding" by De Campos et al. (Contribution [7]) investigates and compares the performance of information retrieval (IR) and machine learning (ML) methods, including deep learning, to approach the problem of identifying academic figures who are experts in different domains when a potential user requests their expertise. Several methods that are fully tailored for the problem are presented in the work.

Author Contributions: Conceptualization, E.R.N.-V. and V.G.-D.; writing-original draft preparation, E.R.N.-V.; writing-review and editing, V.G.-D. and E.R.N.-V.; supervision, V.G.-D. and E.R.N.-V.; project administration, E.R.N.-V. and V.G.-D. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: We thank all authors and reviewers for their prompt and effective contributions. We are very grateful to the Editor-in-Chief of the journal for giving us the opportunity to run a Special Issue in *Algorithms*. We also hope that this Special Issue will be of interest to the scientific world.

Conflicts of Interest: The authors declare no conflicts of interest.

List of Contributions:

1. Lin, G.; Zhang, Y. Sparks of Artificial General Recommender (AGR): Experiments with ChatGPT. *Algorithms* **2023**, *16*, 432. https://doi.org/10.3390/a16090432.
2. Ezeife, C.I.; Karlapalepu, H. A Survey of Sequential Pattern Based E-Commerce Recommendation Systems. *Algorithms* **2023**, *16*, 467. https://doi.org/10.3390/a16100467.
3. Panteli, A.; Boutsinas, B. Addressing the Cold-Start Problem in Recommender Systems Based on Frequent Patterns. *Algorithms* **2023**, *16*, 182. https://doi.org/10.3390/a16040182.

4. Chalkiadakis, G.; Ziogas, I.; Koutsmanis, M.; Streviniotis, E.; Panagiotakis, C.; Papadakis, H. A Novel Hybrid Recommender System for the Tourism Domain. *Algorithms* **2023**, *16*, 215. https://doi.org/10.3390/a16040215.
5. Luo, C.; Wang, Y.; Li, B.; Liu, H.; Wang, P.; Zhang, L.Y. An Efficient Approach to Manage Natural Noises in Recommender Systems. *Algorithms* **2023**, *16*, 228. https://doi.org/10.3390/a16050228.
6. Tallapally, D.; Wang, J.; Potika, K.; Eirinaki, M. Using Graph Neural Networks for Social Recommendations. *Algorithms* **2023**, *16*, 515. https://doi.org/10.3390/a16110515.
7. de Campos, L.M.; Fernández-Luna, J.M.; Huete, J.F.; Ribadas-Pena, F.J.; Bolaños, N. Information Retrieval and Machine Learning Methods for Academic Expert Finding. *Algorithms* **2024**, *17*, 51. https://doi.org/10.3390/a17020051.

References

1. Toffler, A. *Future Shock*; Random House: New York, NY, USA, 1970.
2. Anitha, L.; Devi, M.K.; Devi, P.A. A Review on Recommender System. *Int. J. Comput. Appl.* **2013**, *82*, 27–31. [CrossRef]
3. Berger, H.; Denk, M.; Dittenbach, M.; Pesenhofer, A.; Merkl, D. Photo-based user profiling for tourism recommender systems. In Proceedings of the International Conference on Electronic Commerce and Web Technologies, Regensburg, Germany, 3–7 September 2007; pp. 46–55.
4. Esmaeili, L.; Mardani, S.; Golpayegani, S.A.H.; Madar, Z.Z. A novel tourism recommender system in the context of social commerce. *Expert Syst. Appl.* **2020**, *149*, 113301. [CrossRef]
5. Hong, M.; Jung, J.J. Multi-criteria tensor model for tourism recommender systems. *Expert Syst. Appl.* **2021**, *170*, 114537. [CrossRef]
6. Alrasheed, H.; Alzeer, A.; Alhowimel, A.; Shameri, N.; Althyabi, A. A Multi-Level Tourism Destination Recommender System. *Procedia Comput. Sci.* **2020**, *170*, 333–340. [CrossRef]
7. Herlocker, J.L.; Konstan, J.A.; Borchers, A.; Riedl, J. An algorithmic framework for performing collaborative filtering. In Proceedings of the 22nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, Berkeley, CA, USA, 15–19 August 1999; pp. 230–237.
8. Colombo-Mendoza, L.O.; Valencia-García, R.; Rodríguez-González, A.; Alor-Hernández, G.; Samper-Zapater, J.J. RecomMetz: A context-aware knowledge-based mobile recommender system for movie showtimes. *Expert Syst. Appl.* **2015**, *42*, 1202–1222. [CrossRef]
9. Wang, Z.; Yu, X.; Feng, N.; Wang, Z. An improved collaborative movie recommendation system using computational intelligence. *J. Vis. Lang. Comput.* **2014**, *25*, 667–675. [CrossRef]
10. Katarya, R. Movie recommender system with metaheuristic artificial bee. *Neural Comput. Appl.* **2018**, *30*, 1983–1990. [CrossRef]
11. Airen, S.; Agrawal, J. Movie Recommender System Using K-Nearest Neighbors Variants. *Natl. Acad. Sci. Lett.* **2022**, *45*, 75–82. [CrossRef]
12. Kuroiwa, T.; Bhalla, S. Book recommendation system for utilisation of library services. *Int. J. Comput. Sci. Eng.* **2010**, *5*, 207–213. [CrossRef]
13. Núñez-Valdez, E.R.; Quintana, D.; González Crespo, R.; Isasi, P.; Herrera-Viedma, E. A recommender system based on implicit feedback for selective dissemination of eBooks. *Inf. Sci.* **2018**, *467*, 87–98. [CrossRef]
14. Jomsri, P. Book recommendation system for digital library based on user profiles by using association rule. In Proceedings of the Fourth edition of the International Conference on the Innovative Computing Technology (INTECH 2014), Luton, UK, 13–15 August 2014; pp. 130–134. [CrossRef]
15. Celma, Ò.; Serra, X. FOAFing the music: Bridging the semantic gap in music recommendation. *Web Semant. Sci. Serv. Agents World Wide Web* **2008**, *6*, 250–256. [CrossRef]
16. Sánchez-Moreno, D.; Gil González, A.B.; Muñoz Vicente, M.D.; López Batista, V.F.; Moreno García, M.N. A collaborative filtering method for music recommendation using playing coefficients for artists and users. *Expert Syst. Appl.* **2016**, *66*, 234–244. [CrossRef]
17. Vall, A.; Dorfer, M.; Eghbal-zadeh, H.; Schedl, M.; Burjorjee, K.; Widmer, G. Feature-combination hybrid recommender systems for automated music playlist continuation. *User Model. User-Adapt. Interact.* **2019**, *29*, 527–572. [CrossRef]
18. Walter, F.E.; Battiston, S.; Schweitzer, F. A model of a trust-based recommendation system on a social network. *Auton. Agent. Multi. Agent. Syst.* **2008**, *16*, 57–74. [CrossRef]
19. Nguyen, T.T.S.; Lu, H.Y.; Lu, J. Web-Page Recommendation Based on Web Usage and Domain Knowledge. *IEEE Trans. Knowl. Data Eng.* **2014**, *26*, 2574–2587. [CrossRef]
20. Xie, X.; Wang, B. Web page recommendation via twofold clustering: Considering user behavior and topic relation. *Neural Comput. Appl.* **2018**, *29*, 235–243. [CrossRef]
21. Núñez-Valdéz, E.R.; Cueva Lovelle, J.M.; Sanjuán Martínez, O.; García-Díaz, V.; Ordoñez De Pablos, P.; Montenegro Marín, C.E. Implicit feedback techniques on recommender systems applied to electronic books. *Comput. Human Behav.* **2012**, *28*, 1186–1193. [CrossRef]