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E-Mail :
editor.ijasem@gmail.com
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Novel Time-Aware Food Recommender-System Based on Deep Learning and Graph Clustering

[1]MR.RAMA BHADRA RAO MADDU, [2]CHENNAMSETTI LOHITHA NAGA SAI

[1](Associate Professor), MCA, Swarnandhra College

[2]MCA, scholar, Swarnandhra College

ABSTRACT

In the modern era, with increasing demands for personalized experiences, food recommendation systems have garnered significant attention. However,existing recommendation approaches often neglect the temporal dimension, failing to adapt to users' changing preferences throughout the day. To address this limitation, we propose a novel TimeAware Food Recommender System (TAFRS) that integrates deep learning techniques with graph clustering methodologies.

TAFRS leverages deep learning models, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), to capture the sequential and spatial characteristics of food consumption patterns. By analyzing users' historical consumption data, TAFRS learns intricate temporal dynamics, enabling it to discern preferences at different times of the day.

Furthermore, TAFRS incorporates graph clustering algorithms to identify latent connections between food items based on their nutritional profiles, flavor profiles, and user preferences. Through graph-based representations, TAFRS constructs a comprehensive food-item similarity network, facilitating the recommendation process.

1.INTRODUCTION

From personal growth (using a web platform to build professional services) to pleasure (chatting with other users, shopping,

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looking for hotels, travel bargains), the internet is now an integral part of people's everyday lives and is utilized for many purposes. Users' requests can access massive amounts of data from thousands of sources, which introduces significant ambiguity and uncertainty. While efforts to reduce data redundancy have been ongoing for decades, personalization of search results and reduction of noisy information have met with little success. Even for people with entirely distinct profiles and interests, many of these algorithms nevertheless provide the same results. As one of the most effective online customization tools, recommender-systems have recently attracted greater attention from academics. The list of possible uses is enormous, but it may assist with finding the correct service, alleviating information overload, directing the user towards tailored behavior, and locating the user's favorite goods amid massive amounts of data. Items and services are suggested to users based on their interests in a typical recommender-system. As a tool to help people improve their behavior and adopt healthy lifestyles, meal suggestion is an essential part of many lifestyle apps and services. In general, the goal of food recommendation systems is to help people meet their individual dietary needs and other lifestyle demands by providing them with tailored recommendations based on their preferences, the amount of change they want to make, and the time it will take to accomplish those goals [16][18]. Possible reasons for the lack of focus on food recommendation research include cultural differences and the difficulty in predicting people's eating preferences, as opposed to recommendation systems in other areas of leisure and entertainment, such as music, books, and shopping. Despite this, about 60% of all fatalities are attributable to diet- and lifestyle-related diseases. Many people consider making a meal suggestion to be a machine learning problem. In order to construct a useful meal suggestion, it is essential to have a precise understanding of the user's dietary habits. The only way to get people to follow a recommendation—even for health-conscious meal delivery services—is if it tastes good to them.

Predicting a person's preferences and guiding his decision according to established goals are two of the numerous recommender-systems that have been created in the last several decades. Despite prior food

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recommender-systems' impressive success in learning individuals' preferences via mapping users' history encounters with recipes and food products, these systems nevertheless have some limitations.

1) Food components: The majority of earlier food recommender-systems used a collaborative filtering method that did not take food ingredients into account when drawing upon user ratings for meal suggestions. This is because it's common knowledge that people tend to gravitate toward foods that include elements they like. Some crucial parts of the suggestion could be missed because of this. A person may have a strong aversion to certain spices used in the cooking process, even when they love chicken wing dishes. Thus, it's possible that collaborative filtering recommender-systems won't be sufficient to consider the needs and preferences of such a user.

2) The passage of time: Conventional recommender systems assume that users' future choices will mirror their prior ones. Consequently, many recommender-systems rely on static data and fail to take into account the fact that users' dietary habits, tastes, and overall way of life might vary over time. 3) People that need to start cold-starting their food: The inability of conventional food recommender systems based on collaborative filtering to identify nearby active users or comparable items is mostly attributable to users' tendency to evaluate infrequent meals. As a result, consumers cannot get meal recommendations from collaborative filtering systems unless they have rated a sufficient number of items. So, we don't take into account cold start consumers who haven't rated many foods. Similarly, this collaborative filtering-based method also disregards new food items (food cold start) that haven't garnered enough evaluations from people just yet.

The fourth problem is the user's neighborhood or community component, which is currently disregarded by recommender systems. The community feature may be used to extrapolate the local behaviors of active users to forecast the success probability of a diet and the rating of unseen food items. Models based on clustering are usually adequate for dealing with community aspects. However, it has also been shown that other additional issues, such

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as the ideal number of clusters and the effectiveness of the similarity metrics used, are inherently intrinsic to the clustering algorithms that are used in this approach.

2.LITERATURE SURVEY

Food elements: A majority of earlier food recommender-systems [29], [30] used a collaborative filtering technique that relied on user ratings to generate meal suggestions, ignoring food components. The reasoning for this is based on the fact that people tend to gravitate towards foods that include elements they like. Some 00crucial parts of the suggestion could be missed because of this. A person may have a strong aversion to certain spices used in the cooking process, even when they love chicken wing dishes. Thus, it's possible that collaborative filtering recommender-systems won't be sufficient to consider the needs and preferences of such a user.

The passage of time: Conventional recommender systems assume that users' future choices will mirror their prior ones. As a result, many recommender-systems rely on static data and fail to take into account the fact that users' dietary habits, tastes, and lifestyle choices may and likely will evolve over time.

Thirdly, "cold start" users and "cold start" foods: Old-school food recommender systems that relied on collaborative filtering had a hard time picking up on active user neighbors or comparable foods as users only evaluate a small subset of foods. This means that consumers who have not rated enough items will not get any recommendations from collaborative filtering-based food recommendation systems. So, we don't take into account cold start consumers who haven't rated many foods. Similarly, this collaborative filtering-based method also disregards new food items (food cold start) that haven't garnered enough evaluations from people just yet.

Fourthly, the user's local or community element is another problem that current recommender-systems overlook. The community feature may be used to extrapolate the local behaviors of active users to forecast the success probability of a diet and the rating of unseen food items. Models based on clustering are usually adequate for dealing with community aspects. It has been shown, however, that this method is not without its own set of problems, some of which are intrinsic to the clustering algorithms used.

.3. EXISTING SYSTEM

1) *Ingredients of foods:* Most previous food recommender-systems [29], [30] rely primarily on historical ratings of users to draw upon food recommendations through a collaborative filtering approach that ignores food ingredients. This is due to the observation that a given food is usually preferred by an individual because it contains ingredients, he/she may like to eat. This may overlook some important aspects in the recommendation. For example, foods containing chicken wings may be a person's favorite food, while he/she may be allergic to some types of spices that can be used during the food preparation. Therefore, collaborative filtering recommender-systems may not be enough to account for such user's preferences and constraints.

2) *Time factor:* Traditional recommender-systems [19], [26]_[28] are based on the premise that users with similar preferences in the past will have similar tastes in the future. Accordingly, these recommender-systems use static data and ignore potential changes in user's food preferences, diet or life style that can occur over time in realistic scenarios.

3) *Cold start users and cold start foods:* Due to the fact that users often rate just a few foods, traditional collaborative filtering-based food recommender systems have difficulty recognizing active user neighbors or similar foods. Accordingly, collaborative Filtering-based food recommendation are only able to suggest foods to users who have rated enough foods. Cold start users, who have rated only few food items, are thereby ignored. Similarly, new food items (food cold start) that have not attracted yet enough ratings from users are ignored as well by such a collaborative

filtering-based approach.

4) *Users' community:* Another issue, which is again ignored in existing recommender-systems, is the user's neighborhood or community aspect. Intuitively, community aspect can be utilized to predict the rating of unseen food item and the success likelihood of a given diet, extrapolating from active users' activities in the neighborhood. Typically, community aspect can be handled using clustering-based models. Nevertheless, it has been shown that such an approach also

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suffers from several other difficulties as well, which are somehow inherent to clustering techniques employed (e.g., optimal number of clusters, efficiency of similarity measures employed).

3.1 PROPOED SYSTEM:

1**)***Ingredientsawarefoodrecommender-system:* Unlike traditional collaborative-based food recommender systems, our model integrates both collaborative filtering-based model (user-based phase) and content-based model (food-based phase). As a result, a set of foods that both suit the user's preferences and utilize his/her previous ratings are recommended.

2) *Time-aware food recommender-system:* A novel time-aware similarity measure that takes into account changes in food preferences or diet over time is developed in this paper. This makes the proposal suitable to handle cases where users change his/her rating / preferences over time.

3) *Trust-aware food recommender-system***:** A trust-aware food recommender-system is developed to overcome the cold start user and cold start foods problems of the traditional collaborative filtering-based food recommender-systems. Our proposed model builds a trust network of users based on trust (follower following)

statements to predict user ratings efficiently.

The trust network generation plays an important role in addressing the neighbor selection problem. Trust statements can be used to predict the rating of unseen items

in food recommender-systems since there is a high correlation between users' trust and user ratings-based similarity measure. The user's trust network and the user ratings-based similarity are integrated in this study to address the data sparsity problem utilizing knowledge that is stored outside of the user's local neighborhood

of similarity.

4) *Community-aware food recommender-system:* Contrary to previous works where users' communities are not considered in the food recommendation process, our model explicitly accounts for such aspects where the optimal number of users' clusters is determined automatically. Moreover, using a graphical like representation

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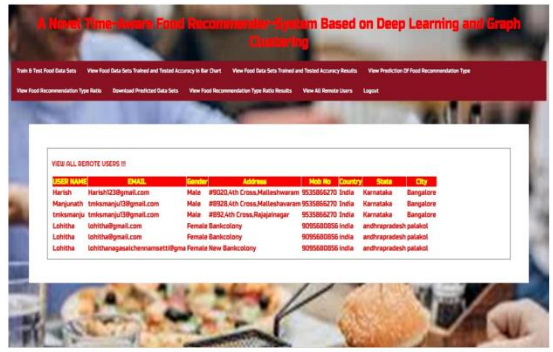
where edge weights are calculated according to user ratings-based similarity and trust network, the proposed method accommodates sparse datasets.

4. OUTPUT SCREENS

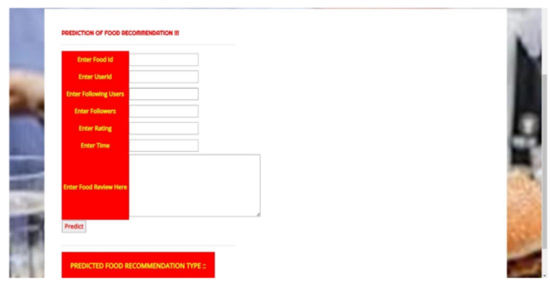
Homepage:

View profile page:

View Remote Users:



Output:



5. CONCLUSION

With the expansion of the web and the amount of people using it, recommender systems that choose products that are relatively suitable for consumers' demands are progressively gaining traction. Many lifestyle services depend on food recommender systems, which are used by a range of lifestyle apps. To address the drawbacks of existing food recommender-systems—such as those that fail to take into account time stamps, cold start users, cold start foods, and user communities—this

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article describes the development of a new hybrid food recommender-system. The suggested solution tackles all four difficulties concurrently and tries to enhance the ultimate accuracy of the recommender-system. It does this by using user-based and content-based models, temporal information, trust networks, and user communities. Suggestion based on food composition and suggestion based on user are the two parts of the suggested technique. The first step incorporates graph clustering, while the second uses a deep-learning based method to group people and food items together. On five separate metrics—Precision, Recall, F1, AUC, and NDCG—the model was compared against the most recent suggested food recommender-systems, which included LDA, HAFR, and FGCN approaches.Based on the trial findings, the created food recommender-system significantly outperformed the state-of-the-art food recommender-systems. Our long-term goal is to enhance the meal recommendation system's effectiveness by including user-side data (such as gender, age, weight, height, location, and culture) into the system.

As an added bonus, healthy eating habits help alleviate the symptoms of many non-infectious disorders. Our long-term goal is to tailor meal recommendations to each individual's unique health situation by extracting useful information from the nutritional profiles of foods.

6.REFERENCES

[1] S. Wang, L. Cao, Y. Wang, Q. Z. Sheng, M. A. Orgun, and D. Lian,
``A survey on session-based recommender systems,'' ACM Comput. Surv.,
vol. 54, no. 7, pp. 138, Sep. 2022.

[2] P. Wang, Y. Wang, L. Y. Zhang, and H. Zhu, ``An effective and efcient
fuzzy approach for managing natural noise in recommender systems,'' Inf.
Sci., vol. 570, pp. 623637, Sep. 2021.

[3] A. D. Viniski, J. P. Barddal, A. D. S. Britto, Jr., F. Enembreck, and
H. V. A. D. Campos, ``Acase study of batch and incremental recommender
systems in supermarket data under concept drifts and cold start,'' Expert
Syst. Appl., vol. 176, Aug. 2021, Art. no. 114890.

[4] X. Yu, Y. Chu, F. Jiang, Y. Guo, and D. Gong, ``SVMs classication based
two-side cross domain collaborative ltering by inferring intrinsic user and

item features," Knowl.-Based Syst., vol. 141, pp. 8091, Feb. 2018.

[5] N. Hazrati and F. Ricci, ``Recommender systems effect on the evolution of users' choices distribution," Inf. Process. Manage., vol. 59, no. 1, Jan. 2022, Art. no. 102766.

[6] L. Xie, Z. Hu, X. Cai, W. Zhang, and J. Chen, ``Explainable recommendation based on knowledge graph and multi-objective optimization," Complex Intell. Syst., vol. 7, no. 3, pp. 12411252, Jun. 2021.

[7] M. Wasid and R. Ali, ``A frequency count approach to multi-criteria recommender system based on criteria weighting using particle swarm optimization," Appl. Soft Comput., vol. 112, Nov. 2021, Art. no. 107782.

[8] S. Forouzandeh, M. Rostami, and K. Berahmand, ``A hybrid method for recommendation systems based on tourism with an evolutionary algorithm and topsis model," Fuzzy Inf. Eng., vol. 14, no. 1, pp. 2650, 2022.

[9] S. Forouzandeh, M. Rostami, and K. Berahmand, ``Presentation a trust Walker for rating prediction in recommender system with biased random walk: Effects of H-index centrality, similarity in items and friends," Eng. Appl. Artif. Intell., vol. 104, Sep. 2021, Art. no. 104325.

[10] T. N. T. Tran, A. Felfernig, and N. Tintarev, ``Humanized recommender systems: State-of-the-art and research issues," ACM Trans. Interact. Intell. Syst., vol. 11, no. 2, pp. 141, Jul. 2021.

[11] M. Slokom, A. Hanjalic, and M. Larson, ``Towards user-oriented privacy for recommender system data: A personalization-based approach to gender obfuscation for user proles," Inf. Process. Manage., vol. 58, no. 6, Nov. 2021, Art. no. 102722.

[12] X.Yu, F. Jiang, J. Du, and D. Gong, ``Across-domain collaborative ltering algorithm with expanding user and item features via the latent factor space of auxiliary domains," Pattern Recognit., vol. 94, pp. 96109, Oct. 2019.

[13] M. Ge, F. Ricci, and D. Massimo, ``Health-aware food recommender system," in Proc. 9th ACMConf. Recommender Syst., Sep. 2015, pp. 333334.

[14] D. Bianchini, V. De Antonellis, N. De Franceschi, and M. Melchiori,

ISSN2454-9940

www.ijasem.org

Vol 18, Issue 2, 2024

``PREFer: A prescription-based food recommender system,'' Comput. Standards Interfaces, vol. 54, pp. 6475, Nov. 2017.

[15] M. B. Vivek, N. Manju, and M. N. Vijay, ``Machine learning based food recipe recommendation system,'' in Proc. Int. Conf. Cogn. Recognit. Singapore: Springer, 2018, pp. 1119.

[16] T. N. T. Tran, A. Felfernig, C. Trattner, and A. Holzinger, ``Recommender systems in the healthcare domain: State-of-the-art and research issues,'' J. Intell. Inf. Syst., vol. 57, no. 1, pp. 171201, Aug. 2021.

[17] M. Premasundari and C. Yamini, ``Food and therapy recommendation system for autistic syndrome using machine learning techniques,'' in Proc. IEEE Int. Conf. Electr., Comput. Commun. Technol. (ICECCT), Feb. 2019, pp. 16.

[18] J.-C. Kim and K. Chung, ``Knowledge-based hybrid decision model using neural network for nutrition management,'' Inf. Technol. Manage., vol. 21, no. 1, pp. 2939, Mar. 2020.

[19] R. Y. Toledo, A. A. Alzahrani, and L. Martinez, ``A food recommender system considering nutritional information and user preferences,'' IEEE Access, vol. 7, pp. 9669596711, 2019.

[20] S. Barko-Sherif, D. Elsweiler, and M. Harvey, ``Conversational agents for recipe recommendation,'' in Proc. Conf. Hum. Inf. Interact. Retr., Mar. 2020, pp. 7382.

[21] Z. Li, J. Hu, J. Shen, and Y. Xu, ``A scalable recipe recommendation system for mobile application,'' in Proc. 3rd Int. Conf. Inf. Sci. Control Eng. (ICISCE), Jul. 2016, pp. 9194.

[22] H. I. Lee, I. Y. Choi, H. S. Moon, and J. K. Kim, ``A multi-period product recommender system in online food market based on recurrent neural networks,'' Sustainability, vol. 12, no. 3, p. 969, Jan. 2020.

[23] W.-Y. Chao and Z. Hass, ``Choice-based user interface design of a smart healthy food recommender system for nudging eating behavior of older adult patients with newly diagnosed type II diabetes,'' in Proc. Int. Conf. Hum.-Comput. Interact. Cham, Switzerland: Springer, 2020, pp. 221234.

[24] V. S. Vairale and S. Shukla, ``Recommendation framework for diet and

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN2454-9940

www.ijasem.org

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exercise based on clinical data: A systematic review," in Data Science and Big Data Analytics. Singapore: Springer, 2019, pp. 333346.