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Cutting-Edge Time-Sensitive Food Recommender System Utilizing Deep Learning and Graph Clustering

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Abstract

There is a consensus that food recommender systems can positively influence dietary habits, guiding users towards healthier choices. This project aims to innovate upon existing meal suggestion methods by disregarding conventional criteria such as nutritional value, community preferences, time constraints, and specialty foods. The proposed system comprises two main components: automated meal ideas based on content and user-generated dinner recommendations. Initially, graph clustering categorizes food items and consumers into groups, followed by the application of machine learning techniques. Furthermore, a meticulous approach evaluates temporal and community-specific factors to enhance the quality of meal plans delivered to users. Analysis of "Allrecipes.com" data confirmed the effectiveness of the suggested cooking recommendation methodology.

Keywords: Ingredients in food, temporal considerations, new users and items, and community elements

1. Introduction

Due to advanced technology, the internet has transformed into a vast network of interconnected computer systems facilitating data transfer and modification. These systems have gained popularity among online shoppers for their ability to generate personalized product recommendations based on user profile information and current interests. The primary aim of recommendation systems is to provide users with relevant and actionable suggestions. However, navigating the extensive food-related data available on the internet, including cooking websites and social media platforms, poses challenges in locating specific gourmet meals. Internet-based food enhancement solutions are on the rise, with food recommender systems (RS) gaining traction. These systems, utilized in various sectors such as online retail, social networking, and entertainment services like music and video streaming, curate content tailored to user preferences and choices. This personalized approach fosters a connection between the consumer and the product, facilitating the delivery of pertinent recommendations.

The importance of meal recommendations in the food industry is growing as they enable consumers to swiftly identify items aligning with their interests. RS, as highlighted by Elahi, Lim, and Zaveri (2023), is integral in enhancing user experience across diverse online platforms. Companies like Alibaba, Amazon, and eBay were early adopters of RS, leveraging these sophisticated technologies to enhance the e-commerce experience.

The rapid global spread of COVID-19 has further underscored the need for expanded use of e-commerce recommendation algorithms to leverage vast amounts of consumer data for personalized product recommendations. Oyebode and Orji (2020) emphasize that RS not only suggest products previously unpurchased by consumers but also expedite the discovery of specific items sought by them, particularly in times of rapid lifestyle adjustments.

Research by Gao et al. (2020) and Li et al. (2023) demonstrates that food recommender systems (FRS) play a significant role in promoting healthier lifestyle choices. These systems in the health and food sectors efficiently categorize and manage extensive data, encouraging healthy eating habits, generating new recipes, and offering tailored meal suggestions. By tracking consumption patterns, FRS can also identify potential health concerns and support overall well-being.
In essence, recommendation systems have revolutionized how consumers interact with digital platforms, offering personalized experiences that enhance user satisfaction and drive engagement across various industries, particularly in the dynamic realm of food and health. Background and concept of the project

2. Sections of The Recommendation Procedure

Information gathering involves collecting and storing data to enable recommendation systems to function effectively. Obtaining relevant data is crucial as the initial step in developing such systems. There are three main approaches—explicit, implicit, and hybrid—used to gather knowledge from users. Explicit input data, like reviews, comments, and ratings, provides valuable insights into user preferences and opinions once collected (Kumar et al., 2019). Implicit input data, such as browser logs, clickstream data, and transaction records, is readily accessible within the system but may not be as reliable as explicit input since it does not originate directly from users (Isinkaye et al., 2015).

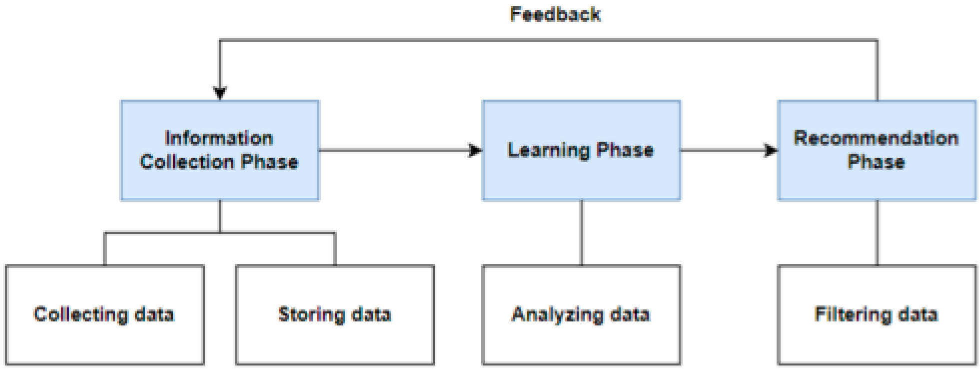

Fig. 1 The steps of creating a tip are as follows.

Feedback comes in direct and indirect forms, with hybrid feedback combining both approaches to enhance accuracy. Integrating data from various sources helps recommendation systems better understand user preferences, behaviors, and dislikes (Kumar et al., 2019). Recommendations are typically made through three primary methods: hybrid-based, content-based, and collaborative filtering (CF/CB). Content-based (CB) filtering, for instance, uses attributes of items to suggest content aligned with user profiles and preferences (Isinkaye et al., 2015).

Vector space models, including techniques like Decision Trees, Neural Networks, Term Frequency-Inverse Document Frequency (TF-IDF), and Naive Bayes algorithms, transform textual data into numerical representations to train machine learning models for recommendation purposes (Zhang et al., 2020).

Collaborative filtering (CF) leverages user ratings and behaviors to predict preferences based on similar users' experiences, aiming to recommend items that align with collective tastes (Zhang et al., 2020; Tran et al., 2018). Matrix factorization (MF) techniques, such as item-based and model-based approaches, address challenges like data sparsity and enhance recommendation accuracy (Bokde et al., 2022).

BACKGROUND WORK

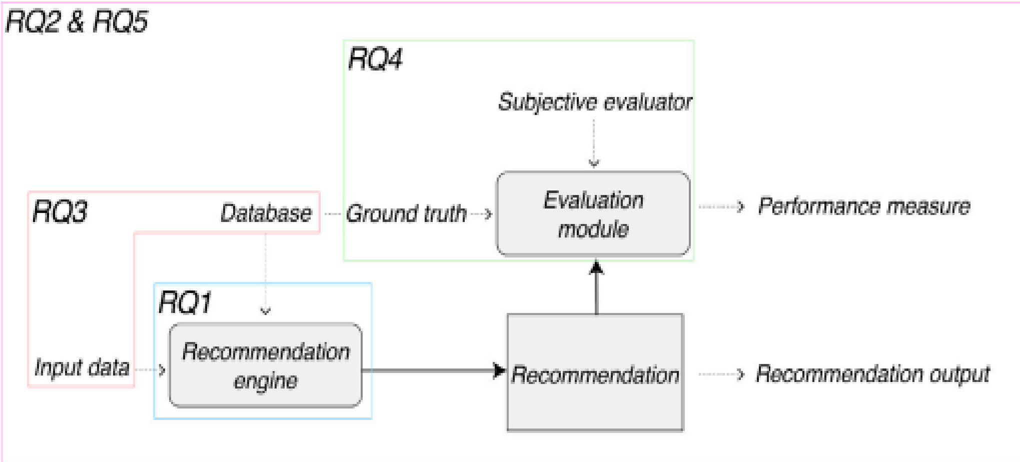

Fig. 2. The FRS employs a comprehensive design, as illustrated Connections between RQs and key components of the system are established.

Food Recommender Systems (FRS), as described by Meng et al. (2020) and Trang Tran et al. (2018), are computational models designed to suggest food items based on specific characteristics or dietary preferences, often inferred from user interactions with the system (Xie & Lou, 2022). Meng et al. (2020) emphasize that food recommendations can be tailored based on learned preferences, considering factors like ingredients, cooking methods, and nutritional content.

FRS typically compare input data against a designated database to evaluate concepts, either objectively or subjectively. Figure 2 illustrates a comprehensive FRS framework, establishing connections between system requirements and key components.

At a fundamental level, FRS can be categorized into two main types, depicted in Figure 2. The first type bases recommendations on explicit user preferences and needs, incorporating factors such as recipe ratings, historical data, and location information to suggest similar food items through similarity metrics.

Alternatively, the second type of FRS relies solely on food attributes to recommend meal options, retrieving these attributes directly from queries. This method assumes sufficient data availability to generate suggestions, regardless of explicit user input, yet it may still consider user preferences, providing unique recommendations tailored to each individual from identical queries.

3. Recommendation Methods

The recommendation process in FRS employs logical reasoning to generate ideas or recipes based on identified characteristics, categorized into four main types according to Bai et al. (2019) and Ghannadrad et al. (2022): collaborative filtering, content-based filtering, graph-based methods, and hybrid methods.
Content-based filtering assesses similarities between content items or between content and user profiles to generate recommendations (Amami et al., 2016; Ghannadrad et al., 2022). It assumes that users prefer recommendations similar to items they already like, determining relevance through shared attributes and logical inference (Lops et al., 2011).

Collaborative filtering algorithms, as discussed by Bai et al. (2019) and Zhang et al. (2021), recommend items by comparing user profiles for similarities. Users with comparable interests are more likely to be interested in the same products, employing various methods to assess similarity and propose new items based on detected similarities with other users.
Graph-based methods visualize connections between users and items through graphs, utilizing vertices to represent users and items and edges to illustrate relationships (Bai et al., 2019). These methods integrate diverse data sources to evaluate meal recommendations based on ingredient co-occurrences and user-recipe relationships.

Hybrid methods combine multiple recommendation approaches to capitalize on their respective strengths, enhancing recommendation accuracy and effectiveness across different contexts (Bai et al., 2019; Ghannadrad et al., 2022). The integration of these methods depends on strategic implementation to optimize system performance.

4. Recommendation Algorithms

Algorithms define the procedures for calculating and retrieving individual recommendations based on fundamental concepts and features used in recommendation systems, categorized into machine learning, statistical, and query-based methods.

Machine learning algorithms apply predictive techniques to generate suggestions based on user or food product attributes (Gallo et al., 2022). Statistical methods quantify similarities between users, food items, or both, determining recommendations through collected statistics.

Query-based algorithms directly retrieve data from food product databases using predefined parameters to organize and filter information accurately. These algorithms predict associations between users, food items, or both through advanced database techniques.

5. Evaluation

Evaluation assesses the quality of recommendations using specific metrics categorized by Ghannadrad et al. (2022) into online, offline, and hybrid methods. Online evaluations measure user engagement with recommendations in real-time, while offline evaluations use controlled datasets to test recommendation accuracy. Evaluation metrics, including accuracy-based, ranking-based, and error-based measurements, quantify the precision, relevance, and performance of FRS recommendations across different scenarios.

6. Experimental Results

Figure 3: An analysis of performance that concentrated on temporal characteristics.

Figure 3 illustrates the performance comparison of food recommendations with and without timestamps incorporated into the recommendation process. It clearly demonstrates that our time-aware meal recommender system outperforms the time-agnostic counterpart in terms of rating accuracy. Specifically, metrics such as NDCG@10, Precision@10, Recall@10, and F1@10 improved by 21.13%, 20.72%, 18.13%, and 11.38%, respectively. Our evaluation utilized these metrics to assess the performance of various meal recommendation systems.

We conducted a thorough investigation to assess the effectiveness of our developed EHFRS (Enhanced Health-Focused Food Recommender System). Our study systematically gathered data from the culinary-focused online community www.Allrecipes.com, spanning from 2000 to 2018 and encompassing information on 52,821 food items available on the website. Gao et al. (2019) collected data including timestamps, nutritional information, and user comments for each food product. Client satisfaction with various food items was assessed based on their ranking order. In total, we collected data from 68,768 users, 1,093,845 evaluations, and 45,630 food items.

To evaluate the efficacy of the newly developed EHFRS, we employed five common metrics: F1, AUC (Area Under the Curve), NDCG (Normalized Discounted Cumulative Gain), Precision, and Recall. Evaluating recommender systems for accuracy and effectiveness poses challenges due to the subjective nature of user ratings, which define the relative value of different items.

7. Experimental Setup and Performance Comparison

In our experimental setup, depicted in Figure 3, we focused on temporal characteristics to analyze performance. We compared our EHFRS model with several state-of-the-art meal recommendation techniques: Graph Convolutional Network (FGCN) (Gao et al., 2022), Hierarchical Attention Food Recommendation (HAFR) (Gao et al., 2019), and Collaborative Filtering Recipe Recommendations (CFRR) (HGAT) (Tian et al., 2022).

Method	Precision	Recall	F1	AUC	NDCG
HAFR	0.0692	0.0671	0.0687	0.6439	0.0451
CFRR	0.0671	0.0647	0.0637	0.6421	0.0431
HGAT	0.0672	0.0649	0.0638	0.6431	0.0436
FGCN	0.0710	0.0681	0.0695	0.6639	0.0462
EHFRS	**0.0739**	**0.0703**	**0.0717**	**0.6884**	**0.0512**

Table 1: The effectiveness of different meal ideas.

Table 1 presents a comparative analysis of the effectiveness of different techniques for food recommendation. The newly developed EHFRS model surpassed all previously established algorithms across all evaluation metrics. Specifically, our method outperformed the second-best food recommender system (FGCN) by margins of 4.08%, 3.23%, 3.16%, 3.69%, and 10.82% in terms of Precision@10, Recall@10, F1@10, AUC, and NDCG@10, respectively. This test confirmed the significance of the γ parameter in EHFRS, set to 0.2, which regulates the influence of nutritional parameters on recommendations.

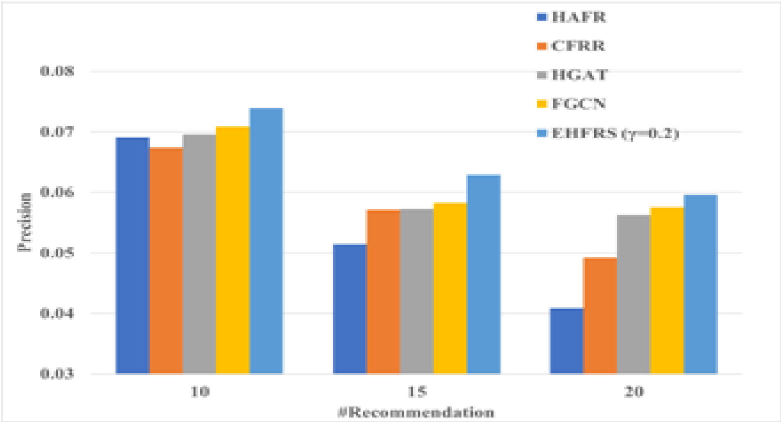

Figure 4: The accuracy of Top-N's dietary recommendations.

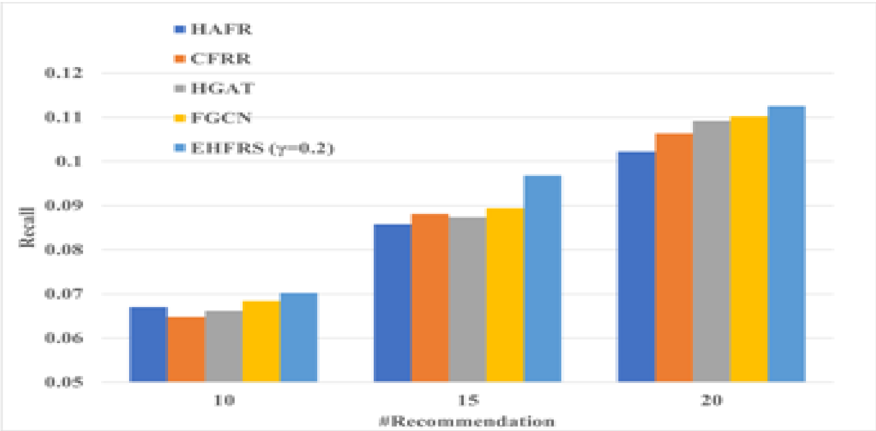

Figure 5: Remember the recommendations made by Top-N.

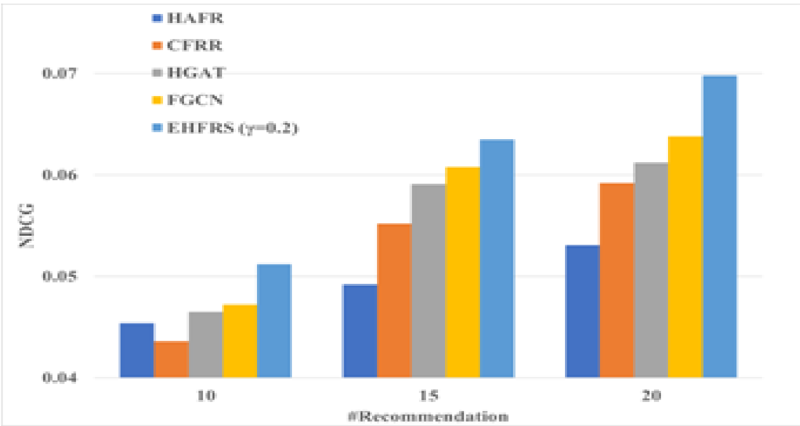

Figure 6: The NDCG gives a list of suggested foods, sorted by NDCG score.

Further investigation explored the impact of varying recommendation list sizes (10, 15, and 20 items) on the performance metrics of several meal recommender systems. Figures 4–6 depict how increasing the list size affects NDCG, Recall, and Precision, showing improvements in these metrics with larger recommendation lists.

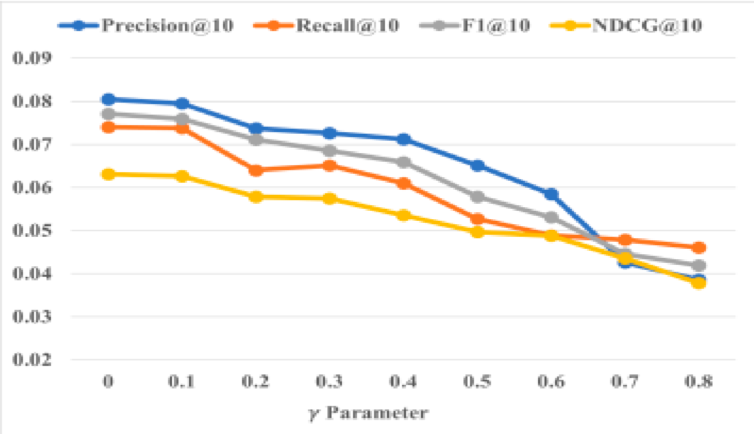

Figure 7: Health-related success review.

Figure 7 illustrates the influence of health-related parameters on system performance. As the γ parameter increased from 0 to 0.8, reflecting the emphasis on health considerations in recommendations, metrics such as NDCG@10, Precision@10, Recall@10, and F1@10 experienced reductions of 40.09%, 52.02%, 37.73%, and 45.58%, respectively.

In conclusion, our study underscores the effectiveness of EHFRS in delivering enhanced food recommendations, supported by rigorous evaluation against established benchmarks and exploration of parameter impacts on recommendation quality.

8. Conclusion

Due to the growing number of internet users and its widespread popularity, many individuals are purchasing recommended products based on their usefulness. Food recommendation systems play a crucial role in various lifestyle services and can serve diverse purposes. This research proposes an innovative and more effective approach to recommending blended meal options. It addresses previous system limitations by considering factors such as food ingredients, timestamps, new users, products, and user classifications simultaneously. The solution leverages temporal data, trust networks, user groups, as well as content- and user-based models to enhance the performance of the recommender system. Adopting a balanced diet has the potential to mitigate symptoms associated with no communicable diseases. Our objective is to provide personalized meal recommendations that account for individuals' nutritional needs and health concerns, aiming to support their overall well-being.

References

1. M. Ge, F. Ricci, and D. Massimo, "Health-conscious food recommendation system," in Proceedings of the 9th ACM Conference on Recommender Systems, September 2015, pp. 333-334.
2. T. N. T. Tran, A. Felfernig, C. Trattner, and A. Holzinger, "Recommendation systems in healthcare:

Current state and research challenges," Journal of Intelligent Information Systems, vol. 57, no. 1, pp. 171-201, August 2021.
3. M. Premasundari and C. Yamini, "Recommendation system for food and therapy in autism using machine learning techniques," in Proceedings of the IEEE International Conference on Electrical, Computer, and Communication Technologies (ICECCT), February 2019, pp. 16.
4. S. Barko-Sherif, D. Elsweiler, and M. Harvey, "Conversational agents for recommending recipes," in Proceedings of the Conference on Human Information Interaction and Retrieval, March 2020, pp. 73-82.
5. H. I. Lee, I. Y. Choi, H. S. Moon, and J. K. Kim, "Multi-period recommender system for products in online food markets using recurrent neural networks," Sustainability, vol. 12, no. 3, p. 969, January 2020.
6. C. C. Aggarwal, "Model-based collaborative filtering," in Recommender Systems, Springer International Publishing, 2016, pp. 71-138.
7. S. Alian, J. Li, and V. Pandey, "Personalized recommendation system supporting diabetes self-management for American Indians," IEEE Access, vol. 6, pp. 73051-73059, 2018.
8. H. G. Andika, M. T. Hadinata, W. Huang, I. A. Iswanto, "Systematic Literature Review: Comparison of collaborative filtering algorithms for recommendation systems," in Proceedings of the IEEE International Conference on Communication, Networks, and Satellite, 2022, pp. 56-61.
9. M. Ashraf, S. S. Sohail, B. M. Chaudhry, "Challenges and opportunities in food recommendation systems," in Proceedings of the International Conference on Data Analytics for Business and Industry, 2022, pp. 570-574.
10. K. Chung, R. Boutaba, S. Hariri, "Knowledge-based decision support systems," Information Technology and Management, vol. 17, nos. 1-3, 2016.
11. X. Gao, F. Feng, X. He, H. Huang, X. Guan, C. Feng, "Hierarchical Attention Network for visually-aware food recommendation," IEEE Transactions on Multimedia, vol. 22, no. 6, pp. 1647-1659, 2020.
12. D. A. Lawlor and N. Pearce, "Vienna declaration on nutrition and non-communicable diseases," 2013.
13. A. E. Majjodi, A. D. Starke, C. Trattner, "Examining the impact of nutrition labels and personalization in a recipe recommender system," in Proceedings of the ACM Conference on User Modeling, Adaptation and Personalization, 2022, pp. 48-56.
14. A. A. Metwally, A. K. Leong, A. Desai, A. Nagarjuna, D. Perelman, M. Snyder, "Learning personal food preferences via food logs embedding," in Proceedings of the IEEE International Conference on Bioinformatics and Biomedicine, 2021, pp. 2281-2286.