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A Time-Aware, Deep Learning-Powered Food Recommendation System

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ABSTRACT

It is widely accepted that food recommender-systems can be useful in encouraging people to adopt better dietary behaviours. This paper's goal is to create a new mixed food recommender-system that improves upon the flaws of existing ones by taking into account factors like time, user and food preferences, and community context. The suggested procedure has two parts: the first is a user-based suggestion, and the second is a recommendation based on the food's substance. In the first stage, users and food items are clustered using graph clustering, and in the second stage, users and food items are clustered using a deep-learning based method. In addition, a comprehensive method is used to enhance the suggestion quality by taking into consideration time and user-community associated problems. We used five different performance metrics—Accuracy, Precision, Recall, F1, and NDCG—to evaluate our model against a collection of state-of-the-art recommender-systems. A sample taken from ''Allrecipes.com'' was used to conduct experiments, and the results showed that the created meal recommender-system was the most effective.

Keywords

Topics covered include: recommender systems, network grouping, deep learning, healthcare, and recommending foods.

INTRODUCTION

To relax (i.e., chatting with other users, buying, looking for lodgings, hunting for travel offers) or advance one's career (i.e., using a web platform to create professional services), the internet has become an integral component of people's everyday routines [1]-[4]. Massive doubt and misunderstanding, which can easily deviate the user from his initial request [5]-[7], are created by the tens of thousands of sources a user can access as part of his/her request. In spite of search engines' best efforts over the past few decades to personalize search results and minimize noise information, little progress has been made on either front [8, 9]. When used by people with vastly diverse backgrounds and preferences, these systems often produce the same outcomes. One of the most popular methods of online customization, recommender-systems have attracted increased attention from academics in recent years [10, 12]. Among its many applications is aiding the user in locating their preferred things within a large database of information and determining which service will best meet their needs. Users' preferences are used to make product and service recommendations in a recommender-system. Food recommendation is a powerful instrument in a number of lifestyle apps and services [13]-[15] that encourage users to make positive lifestyle changes. Recipes, the degree of change, and the amount of time invested in order to meet particular dietary or living goals are typically the primary focus of food suggestion services [16]–[18]. Unlike other forms of recommendation study (e.g., audio, book, and purchasing suggestion systems), food recommendation has historically received little focus.

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This could be due to societal obstacles and the challenge of predicting what people might like to consume. Obesity and diabetes are just two examples of lifestyle and diet-related diseases that contribute to the nearly 60% of all fatalities [19]. Machine learning is increasingly seen as a viable option for the job of creating a meal suggestion [20], [21]. That's why it's so important to get a good read on users' culinary tastes before you try to make any solid recommendations. Even when designing health-focused food services, encouraging users to take action depends on whether or not the suggested cuisine is to their liking [22, 25].

BACKGROUND

This section's first half provides a foundational understanding of recommender-systems. This is followed by a short discussion of the problems with and limitations of existing meal recommendation systems.

RECOMMENDER-SYSTEM

Users have less time to look for the information they need due to the increasing amount of information accessible on the World Wide Web and the declining quality of its material [31]-[33]. It is particularly difficult to find a pertinent selection that would draw user interest among the vast number of goods offered by business and/or entertaining online services [34], [35]. Recommender-systems try to make decisions that take into account a user's preferences, actions, and environment [36]. The input methods utilized by recommender-systems range from model and algorithm to final suggestion [37, 40]. For this purpose, examples of possible entry data sources are as follows:

PROFILE OF USER

contains social and economic characteristics that can be used to better recognize and forecast user preferences, such as age, gender, place of origin, schooling, employment, and residence.

User Rating

relates to the weights given to various aspects of an evaluation by users. Likert scale [41] is commonly used for this purpose because it presumes the user's opinion can be recorded on a spectrum from strong agreement to strong disagreement (i.e., value 5 for strong agreement, value 1 for strong disagreement, value 3 for unsure).

REPLY FROM USERS

refer to the written account's users leave on individual things, in which they share their impressions and opinions about those items. In this instance, the system will need Natural Language Processing (NLP) methods to analyse written data and draw meaningful conclusions [42].

METHOD SUGGESTION

In the continuation of this research, we will assume the following: (I) the existence of a user community that conveys a minimum trust level among its individuals; (ii) each user has his own ratings about a set of food items (each food item is consti tuted by a number of ingredients) that describe his own diet preference (s); (iii) a user's preference can potentially change over time, and these historical changes are fully known.

As such, the created recommender-system ought to take the aforementioned three considerations into mind. To achieve this goal, we developed a recommender system called TDLGC, which combines the ideas of Deep Learning (DL) and Graph Clustering (GC) in such a way that it can account for both the confidence networks of users and their recent scores. Overall, as shown in Figure 1, the created model's conceptual structure consists of two stages: (1) Predicting ratings based on users' input and (2) Predicting ratings based on the food being evaluated. In the first step, (I) the user-user resemblance matrix and the users' confidence network are produced by combining the user ranking and the follower-following network. Then (ii) the provided user collection is put onto a weighted graph according to the user commonalities and the confidence network. To further categorize the users, (iii) a new time-aware network grouping method is suggested. Finally (iv), new user-based ratings are forecasted using user groups from step (i), user similarity, and past ratings. In the second step, (I) a deep learning-based method is used to incorporate the culinary components. The commonalities between items are then evaluated (ii) using the corresponding embedding vectors. Finally (iii), based on the commonalities between meals, projected ratings for previously unknown foods are generated. Following these two steps, (iv) the Top-N food will be recommended to the intended user using both the user-based forecast and the food-based prediction. Following the issue statement, we'll dive into the specifics of our suggested meal recommender-system's various iterations.

RESULTS OF EXPERIMENTS

Several trials are devised in this part to evaluate the effectiveness of the created meal recommender-system. The suggested system is also evaluated in light of existing cutting-edge meal recommendation systems. Information about the dataset, the assessment metrics, the findings, the risk analysis, and the debate are all broken down into their own parts.

DATASET

Current public food databases, such as Food-101 [65] and Yummly [66], are not suitable for evaluating our food recommender-system due to the lack of accessible user-food evaluation information. To that end, we crawled the Allrecipes.com website to gather our user-food review information. It is one of the most popular Food-Related Social Networks online, with 1.5 billion annual views. Between 2000 and 2018, a total of 52,821 culinary items across 27 categories were examined. The user ids, components, ratings, evaluation times, and follower-following connections of each user are scanned for each meal. User interaction with the meal is indicated by a binary tacit response produced based on the ranking of different cuisines. We tallied 1,093,845 evaluations from our 68,768 users, 45,630 meals containing 33,147 components, and their overall popularity. Table 2 lists the primary features of the scanned food collection.

TABLE 1. The main characteristics of the crawled food dataset

Years of crawled data	2000-2018
Number of crawled food category	27
Number of users	68,768
Number of Foods	45,630
Number of ingredients	33,147
Number of ratings	1,093,845

TABLE 2. Part of Food set data

Food ID	Food Name	Raw Ingredients	Output Ingredi-ents
218939	Foolproof Rose-mary Chicken Wings	chicken wings, sprigs rosemary, head garlic, olive oil, lemon pepper, seasoned salt	chicken wing, sprig rosemary, head garlic, olive oil, lemon pepper, season salt
87211	Chicken Pesto Paninis	focaccia bread quartered, prepared basil pesto, diced cooked chicken, diced green bell pepper, diced red onion, shredded Monterey Jack cheese	focaccia bread quarter, prepare basil pesto, dice cook chicken, dice green bell pepper, dice red onion, shred monterey jack cheese
20453	Reuben Sand-wich I	rye bread, butter, thinly sliced corned beef, sauerkraut, mozzarella cheese	rye bread, butter, thinly slice corn beef, sauerkraut, mozzarella cheese
22402	Cranberry Pork Chops II	pork chops, fresh, white sugar, salt, ground black pepper, water	pork chop, fresh, white sugar, salt, ground black pepper, water

In addition, natural language processing is essential for the food-similarity calculation due to the necessity of identifying food ingredients from the scanned text. To accomplish this, we used a basic string-matching method from the NLTK (natural language processing tools) to recognize components against a curated inventory. Before the raw ingredients are used in the major stages of the suggested technique, they are formalized as ingre dients and pre-processed. Tokenization, splitting, and the elimination of stop words are all part of this pre-processing. To filter out unnecessary phrases, we use a predefined "stop words" list and modify it to meet our requirements. Stemming is the process of deconstructing a word into its basic shapes, called stems. For this preliminary processing, this study uses Porter's stemming approach (Porter) [67]. Table 3 displays a subset of the input food set, their basic components, and the final food set. Additionally, the User-Food rating grid is displayed in portion in Table 4.

RESULTS

Several trials are planned to determine how well the meal recommender-system works. We used the Bayesian-based parameter optimization method described in [68] to determine the best settings for the, and parameters in our trials. Accordingly, we use values of 2.5, 0.5, and 0.6 for the, and factors. The first section of our trials assesses the results of our recommender-system's two-stage development process. Table 5 compares the effectiveness of the developed food recommender-system with that of two alternative configurations: one in which recommendations are made solely on the basis of User-based rating prediction, and another in which recommendations are made solely on the basis of Food-based rating prediction. Table 5 demonstrates that when the recommender-system approach is used to forecast the ultimate order based on both the User-based and Food-based stages, it considerably outperforms when used alone. Measures like Precision@10, Recall@10, AUC, and NDCG@10 all show increases of between 12.1 and 16.4 percentage points. The subsequent test will examine the relevance of trust network generation. Performance of the created recommender-system with and without confidence network (follower-following) is reported in Table 6. This chart demonstrates how the suggested recommender technique benefits from taking into account user confidence assertions. In percentage terms, these gains are: 5%, 10%, 12.4%, 3.6%, and 3.1%

TABLE 3. Performance analysis of User-based prediction and Food-based prediction phases in the final recommendation.

	User-based	Food-based	Combination mode
Precision@10	0.0642	0.0621	0.0721
Recall@10	0.0621	0.0613	0.0691
F1@10	0.0611	0.0635	0.0705
AUC	0.6214	0.6112	0.6812
NDCG@10	0.0418	0.0427	0.0497

TABLE 4. Performance analysis of Trust-aware recommender-system in the final recommendation.

	Non-Trust-Aware	Trust-Aware
Precision@10	0.0686	0.0721
Recall@10	0.0627	0.0691
F1@10	0.0663	0.0705
AUC	0.6575	0.6812
NDCG@10	0.0482	0.0497

TABLE 5. Performance analysis of Time-aware recommender-system in the final recommendation.

	Non-Time-Aware	Time-Aware
Precision@10	0.0635	0.0721
Recall@10	0.0614	0.0691
F1@10	0.0621	0.0705
AUC	0.6215	0.6812
NDCG@10	0.0478	0.0497

in terms of NDCG@10, AUC@10, F1@10, and AUC, correspondingly. In the following study, we test how including a time tag in the user-based forecast changes the results. Table 7 shows the results of testing the developed recommender-system with and without taking the ranking timestamp into account. The data shows that the suggested time-aware food recommender-system forecasts scores significantly better than the non-time-aware recommender-system (e.g., 13.4 percentage points better using Precision@10 measure, and 12.5% percentage points better using Recall@10 measure). Three state-of-the-art meal recommender-systems (LDA [29], HAFR [27], and FGCN [26]) are then compared to the created system to gauge its efficacy. Ten independent trials were performed in order to get more accurate results. The dataset is split into three parts for each run: train data (typically 60% of the total), test data (30% of the total), and confirmation data (10% of the total). We evaluate the suggested items using test data after using training and confirmation data for learning. The comparable systems are tested using the same training/testing collection to ensure consistent results.

CONCLUSION

As the Internet expands and more people start using it, recommender systems that tailor product suggestions to individual users' tastes are becoming increasingly common. Food recommender systems are an essential component of many lifestyle services, and are relied on by a wide range of lifestyle apps. In this article, we create an innovative hybrid food recommender-system to address the limitations of existing food recommendation tools, such as their inability to properly account for food components, the passage of time, or the fact that they require both a pre-existing user base and an existing food database to function properly. The suggested approach uses user-based and content-based models in addition to temporal information, a confidence network, and user groups in an effort to enhance the recommender-system's ultimate precision. The suggested technique has two stages: the first is a suggestion based on the food's substance, and the second is a recommendation based on the individual. In the first stage, users and food items are clustered using graph clustering, and in the second stage, users and food items are clustered using a deep-learning based method. The model has been evaluated in terms of five distinct measures (Precision, Recall, F1, AUC, and NDCG) and compared to the most recent suggested meal recommender-system, which includes LDA, HAFR, and FGCN techniques. The created food recommender-system outperformed state-of-the-art food recommender-systems in experiments, showing that it is the finest of its kind. To further enhance the ultimate performance of the food suggestion, we plan to integrate the ancillary information of users (such as gender, age, weight, height, region, and culture) into the food recommendation system in future works. In addition, the severity of symptoms from non-infectious illnesses can be reduced by maintaining healthy dietary habits. Our long-term goal is to tailor dietary recommendations to each individual's health conditions and state using data collected from nutritional analyses of commodities.

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