Innovative Food Recommendation Systems: a Machine Learning Approach

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This thesis is submitted for the degree of

Doctor of Philosophy

May 2023

I would like to dedicate this thesis to my parents.

Declaration

I, Jieyu Zhang, hereby declare that this thesis and the work presented in it are entirely my own. Some of the work has been previously published in journal or conference papers, and this has been mentioned in the thesis. Where I have consulted the work of others, this is always clearly stated.

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May 2023

Acknowledgements

First, I would like to express my sincere gratitude to my supervisors, Prof. Xiaohui Liu and Prof. Zidong Wang, for their consistent encouragement, inspiring motivation, professional guidance, and constant help. They have guided me through the entire process of writing this thesis. Without their unwavering guidance and enlightenment, this thesis would not have achieved its current form. Prof. Xiaohui Liu was consistently encouraging of my explorations in research and provided me with kindly guidance. His guidance, motivation, and patience have always been of tremendous assistance to me throughout my academic journey. I would also like to take this opportunity to express my sincere thanks to Prof. Zidong Wang. His words of encouragement and assistance have been an invaluable source of strength for me.

Second, I would like to express my heartfelt gratitude to the following people for useful discussions, suggestions, comments, and supports of my research during the PhD stage: Dr. Weibo Liu, Dr. Chuang Wang, Dr. Yani Xue, Dr. Nan Hou, Dr. Wei Chen, Dr. Mincan Li. It is my honor to meet you in these years.

Last but not least, I want to express my gratitude to my dear family for their unwavering support, thoughtfulness, and high level of trust in me throughout the years. My parents have always supported me and helped me when I was in need without ever complaining. Their selfless love and concern have motivated me and kept me going.

Abstract

Recommendation systems employ users history data records to predict their preference, and have been widely used in diverse fields including biology, e-commerce, and healthcare. Traditional recommendation techniques include content-based, collaborative-based and hybrid methods but not all real-world problems can be best addressed by these classical recommendation techniques. Food recommendation is one such challenging problem where there is an urgent need to use novel recommendation systems in assisting people to select healthy, balanced and personalized food plans. In this thesis, we make several advances in food recommendation systems using innovative machine learning methods. First, a novel recommendation approach is proposed by transforming an original recommendation problem into a many-objective optimisation one that contains several different objectives resulting in more balanced recommendations. Second, a unified approach to designing sequence-based personalised food recommendation systems is investigated to accommodate dynamic user behaviours. Third, a new food recommendation approach is developed with a temporal dependent graph neural network and data augmentation techniques leading to more accurate and robust recommendations. The experimental results show that these proposed approaches have not only provided a more balanced and accurate way of recommending food than the traditional methods but also led to promising areas for future research.

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Nomenclature

Acronyms / Abbreviations

ANN Artificial Neural Network

CNNs Convolutional neural networks

GRU Gated recurrent unit

CBF Content-based filtering

CF Collaborative Filtering

GNNs Graph Neural Networks

GRU Gated Recurrent Unit

LSTM Long Short-Term Memory

MaOO Many Objective Optimisation

MaOPs many-objective problems

MFP MyFitnessPal

MLP Multilayer Perceptron

MOO Multi-objective optimization

MOPs multi-objective problems

MORS Multi-objective recommender systems

NSGA Non-dominated Sorting Genetic Algorithm

PAES Pareto Archived Evolution Strategy

PCC Pearson correlation coefficient

PPMI Positive Point-wise Mutual Information

RNNs Recurrent Neural Networks

RRS Reciprocal recommendation models

RS Recommendation System

SPEA Strength Pareto Evolutionary Algorithm

SRSs sequence-based recommender systems

TDGNN Temporal Dependent Graph Neural Network

Chapter 1

Introduction

1.1 Motivation

In recent years, people have become increasingly aware of the importance of their health. This heightened awareness has been driven by the significant improvements in living conditions that have been seen across the globe [167]. As access to food resources and nutritional knowledge increases, people are faced with the challenge of making more informed and conscious decisions about their health and wellbeing. Obesity and diabetes, two illnesses influenced by nutrition and lifestyle, account for 60% of all fatalities worldwide.

Food recommender systems (RSs) [44, 82, 110, 156, 158] have been developed to provide personalized recommendations tailored to the user's preferences. By leveraging the power of machine learning algorithms, Food RSs are able to analyse user data and make informed recommendations. These systems have shown their effectiveness in a variety of contexts by enabling users to manage information overload, supporting decision-making, and changing user behaviour. Digital sources for culinary inspiration are growing in popularity, as are systems that propose food-related recommendation, such as recipes, restaurant meals and grocery store items. Food recommendation systems not only provide relevant recommendations that users may wish to eat, but also assist users in consuming a healthier diet. As a result of this, health-aware food recommender systems are often proposed as a significant component of the answers for promoting healthy dietary choices.

Various machine learning techniques, including content-based, collaborative filtering, and hybrid recommendation approaches, have been developed and evaluated in the food domain. Content-based filtering [109, 96] use information about the user's preferences and items they have interacted with to recommend similar items. Collaborative filtering algorithms [78, 146] build a model from a user's past behaviour and compare it to other users' data to make predictions about what the user might like. Hybrid approaches [10, 98]use a combination of both collaborative and content-based filtering algorithms to provide a more accurate recommendation. Food recommendation, however, is a complex task that presents unique challenges. First, because food recommendations are personalized, there is a need to ensure that the recommendations are both diverse and relevant to the user. There are often multiple optimal recommendations depending on circumstances under consideration. Second, since food recommendation is a dynamic task, there is a need to be able to quickly and accurately adapt to meet user preferences where dynamic user behaviour should be taken into account when considering appropriate recommendations. Last but not least, there is a need to accurately capture and represent users' preferences, which can be difficult to do as preferences are often subjective. All of these challenges make food recommendation a very difficult task.

When suggesting food, novelty and serendipity are both important considerations when it comes to food recommendations [75]. Novelty is the idea of introducing something new and exciting to the diner, while serendipity is the concept of providing unexpected yet delightful culinary experiences. Together, these qualities can create a unique and memorable dining experience. By taking into account both novelty and serendipity, food recommendations can be tailored to individual tastes and preferences in a way that is sure to please. Novelty encourages customers to try new dishes, while serendipity introduces them to unexpected items they may not have otherwise considered. By combining both of these elements, food establishments can offer customers exciting culinary experiences that will keep them coming back for more. Furthermore, the preference-healthfulness trade-off is similar to research on novelty and serendipity in that it requires recommending items that are not preferred but healthy. The need to consider many diverse objectives in food recommendation should be taken into account when developing innovative food RSs.

In order to make informed decisions about what to eat, individuals must understand the implications of their dietary choices on their health. This requires an understanding of the nutrients present in the food they are consuming and how they may affect their health. For example, some foods may taste great but lack important vitamins and minerals that are essential for good health. Additionally, some foods may be highly nutritious but lack flavour. Equally important if not more is that a food RSs should be able to adapt its recommendations to each individuals dynamic behaviour over time in order to have best dietary choices for their health and wellbeing.

Furthermore, interpreting user preferences accurately can be a challenging task, as individual preferences tend to be subjective and are often difficult to predict. For example, users may have intricate, limited requirements, like allergies or dietary choices, such as only consuming vegan or vegetarian meals. Other factors to consider include that food items can have various titles, ingredients can be prepared in various styles, and, unlike other domains where items or media are recommended, it is not always apparent if the suggested item can be cooked or eaten because of the potential for limited ingredients, cooking knowledge, or necessary utensils.

1.2 Aim and Objectives

This thesis aims to investigate how to design innovative food recommendation systems that can effectively address existing challenges as discussed above using advanced machine learning methods. There are three main objectives to fulfil this aim:

- To investigate how to present balanced food recommendations by taking into consideration of many desirable but conflicting objectives.
- To study how to make appropriate food recommendations to meet user preferences by adapting to dynamic user behaviour.
- To explore how to make accurate and robust recommendations by considering advanced deep learning and data augmentation techniques.

First, we address the challenge of considering many desirable but potentially conflicting objectives when making food recommendation. We do so through an evolutionary many-objective optimisation framework. In particular, the original recommendation problem is transformed into a many-objective optimisation one that contains four different objectives, leading to more balanced recommendations.

Second, we investigate how the dynamic user behaviours can be taken into account when solving recommendation tasks. Especially we consider the sequentially ordered information from user-item interactions in the food RSs and explore how to develop a sequence-based recommendation model using the long short-term memory networks as the building block and a collaborative filtering unit to make personalized food recommendation.

Third, we explore how to obtain more accurate and robust recommendations. As Graph Neural Networks (GNNs) are capable of capturing the complex interactions between users and items, we will extend a particular type of GNNs called Temporal Dependent Graph Neural Network (TDGNN) with data augmentation techniques in developing food recommendation systems.

1.3 Research Approach

Our research starts with the question "What is the most effective way of making food recommendation?" In order to answer this question, this research aims to identify and evaluate the most efficient techniques for gathering and analysing data on food consumption. Specifically, this research aims to investigate different data analysis techniques, such as machine learning algorithms and statistical methods, and assess their effectiveness in generating personalized food recommendations based on individual dietary needs and preferences.

First, online food consumption data is gathered from various sources such as food tracking apps and websites to attain insight into user eating behaviors and preferences. Various recommendation techniques such as collaborative filtering, content-based filtering, and hybrid methods are employed to analyze the collected data. Subsequently, our work advances the food recommendation task by considering it as a many-objective optimization problem, rather than a single-objective one. By simultaneously optimizing multiple objectives related to food, personalized food recommendations can be more effective and better aligned with an individual's goals and preferences.

After refining the food recommendation task by considering multiple objectives related to food, our work takes a further step to enhance the effectiveness of personalized food recommendations. More precisely, we take into account the sequential behavior of users when making food recommendations. A user's eating behavior is often sequential and ordered, with one meal impacting the next. By considering the sequence of meals and their impact on a user's dietary goals, our work can provide personalized food recommendations that are not only tailored to user preference but also nutritionally balanced and well-suited to their dietary needs and goals.

To enhance our analysis of users' sequential behavior, we have employed graph neural networks (GNNs) to improve our study of users' sequential behavior. The sequence of meals a user consumes over time can be effectively modeled using GNNs, which are a type of deep learning architecture. By representing users' sequential behavior as a graph, we can more precisely depict the relationships, interactions, and impacts of various meals on a user's dietary goals. This approach enables us to consider the complex interactions between multiple factors that influence food consumption patterns, such as taste preferences, and nutritional goals. In particular, a user's eating habits over the course of a week can be represented as a graph, where each node corresponds to a meal the user has had and the connections between the nodes reveal how closely related each meal is to the one before it. This information can be used to develop personalized food recommendations that take into account the user's dietary goals, preferences, and eating patterns, resulting in a more effective and tailored approach to food recommendation.

In summary, our work offers many enhancement strategies for tailored meal suggestions, each of which is assessed in comparison to different baselines. We execute comprehensive trials to assess how well our techniques perform in comparison to these baselines, and the findings imply that our strategies are successful in raising the caliber of food suggestions.

1.4 Contribution

The main contributions of the thesis are summarised as follows:

- We introduce a new food recommendation problem that could offer users with a scientific yet personalized diet where four different food related objectives are required to be simultaneously optimized. A food recommendation framework is then proposed to achieve the recommendation task where the original recommendation task is converted into a Many Objective Optimisation (MaOO) problem and three MaOO approaches are delicately combined to address the challenges. We have conducted extensive experiments using real-world data sets that have shown the new approach provides a more balanced way of recommending food than the classical recommendation methods that only consider individuals food preferences.

- We have proposed a unified food recommendation framework that leverages feedbacks from sequences as well as historical interactions to model users long and short-term preferences. In particular, the Long Short-Term Memory (LSTM) networks have been used to learn high-dimensional user and item representations and a series of computational experiments are conducted on a real-world data set to validate the effectiveness of the developed technique. It is shown that the proposed recommendation system is capable of effectively modelling users long-and short-term preferences and providing more accurate and diverse food recommendation in comparison with existing food recommendation techniques.

- We have transformed the recommendation task into a graph-based link prediction problem resulting in more precise and robust recommendations. In particular, a food recommendation approach is proposed based on Temporal Dependent Graph Neural Network and data augmentation techniques is proposed. Furthermore, data augmentation is introduced in the modelling process to enhance the diversity of data and improve the robustness of the model, and by considering temporal behaviour of user into the network, the accuracy of prediction is further improved. Experimental results evaluated on real-world datasets have shown that the recommendations produced by the system are not only more accurate but also more robust the commonly used recommendation systems.

1.5 Thesis structure

The thesis is structured as follows:

Chapter 2 provides necessary background information for the thesis. In particular, key recommendation techniques are reviewed, including content-based, collaborative filtering (CF)-based, hybrid methods, many-objective optimisation and other methods.

These techniques are discussed in the context of concrete applications including food, biology, e-commerce and healthcare.

In Chapter 3, a novel food recommendation approach is put forward, which transforms the original recommendation problem into a many-objective optimization one with four different objectives, including user preferences, nutritional values, dietary diversity, and user diet patterns. The new food recommendation framework utilises three many-objective optimisation techniques which are evaluated on real-world datasets.

In Chapter 4, a sequence-based recommendation approach is proposed to lay an effective and systematic basis for establishing food recommendation systems. Technically, the long short-term memory networks are employed as the basic skeletons to establish such a recommendation model. After that, a collaborative filtering unit is adopted to make personalized food recommendations. Real-world datasets are used to assess the performance of the proposed approach.

In Chapter 5, to make the food recommendations more accurate and robust, a new food recommendation approach is developed with the facility of temporal dependent graph neural network (TDGNN) and data augmentation techniques, which converts recommendation problems into continuous time prediction tasks. The performance of the proposed approach is evaluated on real-world datasets.

In Chapter 6, the work presented in this thesis is summarized and future research topics are presented.

1.6 Publications

The work resulting from this thesis has been reported in the following papers:

- **J. Zhang**, M. Li, W. Liu, S. Lauria, and X. Liu, Many-objective optimization meets recommendation systems: A food recommendation scenario, *Neurocomputing*, vol. 503, pp. 109117, 2022.
- **W. Yue**, Z. Wang, J. Zhang, and X. Liu, An Overview of Recommendation Techniques and Their Applications in Healthcare, *IEEE/CAA Journal of Automatic Sinica*, vol. 8, no. 4, pp. 701–717, 2021.
- **J. Zhang**, Z. Wang, X. Liu, and Q. Zheng, A Unified Approach to Designing Sequence-Based Personalized Food Recommendation Systems: Tackling Dynamic User Behaviour, *International Journal of Machine Learning and Cybernetics*, https://doi.org/10.1007/s13042-023-01808-7, 2023.

Chapter 2

Background

With the advancement of technology, people have been able to utilize large amounts of data to their advantage, enabling them to make better decisions and save time. However, the vast amount of data also presents challenges in managing this information. Recommendation systems (RSs) have been utilized as an efficient means of enhancing decision-making abilities. Different types of recommendation algorithms are employed in RSs to analyze user behavior data and identify what users are looking for, thereby providing them with products and services that fit their needs [69, 142]. Currently, the cutting-edge recommendation methods can be categorized into three main types: collaborative filtering-based approaches, content-based approaches, and hybrid approaches.

Recently, people from all over the world have become increasingly aware of the importance of health, partly due to the advances in modern society and the rise in quality of life. More and more people are striving to keep their bodies and lifestyles in an optimum health. The widespread adoption of unhealthy habits is one of the main causes of the global spread of chronic illnesses. For example, a sedentary lifestyle can increase the risk of cardiovascular disease, diabetes, and some cancers. Similarly, smoking is linked to higher rates of lung cancer, chronic obstructive pulmonary disease, and cardiovascular disease. Poor nutrition, such as a diet high in processed foods, can increase the risk of obesity, which is associated with an increased risk of many diseases [157, 57].

When it comes to developing tailored solutions to meet the needs of individuals, it is important to consider their unique circumstances and preferences. This means taking into account the individual's lifestyle, environment, and access to resources. It is also important to consider cultural, religious, or socioeconomic factors that may affect an individual's ability to access certain solutions. Additionally, it is crucial to ensure that solutions are tailored to the individual's goals. This includes both short-term and long-term goals. For example, if an individual is looking to improve their physical health, their tailored solution may include a combination of lifestyle changes and access to healthcare. However, if their goal is to maintain their health in the long-term, then their tailored solution may include strategies to increase their physical activity and promote healthy eating habits.

Measuring health outcomes is an essential part of providing individuals with personalized suggestions to improve their health. It is important to have a reliable and accurate way to measure health outcomes so that the suggestions provided can be tailored to the individual's needs and the progress of the individual can be tracked. By measuring health outcomes, the effectiveness of any intervention can be evaluated, and this is a vital part of improving and maintaining the health of any individual. There are many different ways to measure health outcomes, ranging from simple observations to more complex, sophisticated tests. Some examples of measures include self-reported surveys, physical examinations, laboratory tests, medical imaging, and biometric data. Each of these measures has its own advantages and disadvantages, and it is important to select the most appropriate measure for the individual and the specific health outcome being evaluated.

Although food and nutrition are intricate areas that present many difficulties for recommendation systems, they remain a worthwhile endeavor. In order to provide suggestions, a substantial amount of food items/ingredients must be gathered. In addition, due to recipes often combining multiple ingredients which would not typically be eaten individually, the complexity of a recommender system is greatly increased. Moreover, food recommender systems not only present edibles that are tailored to users' tastes, but also provide healthy dietary options, monitor eating habits, recognize health issues, and encourage users to modify their behaviors [140, 13].

In this chapter, we aim to give a comprehensive review of recommendation systems and their application in the food domain. First, a brief introduction of RS is given in Section 2.1. After that, the multi-objective optimization for recommendation system is briefly introduced in Section 2.2. Then, the deep learning-based recommendation system is introduced in Section 2.3.

2.1 Recommendation system

Recommendation task, in its simplest form, may be converted to a matrix completion task. This can be done by predicting the ratings for a given user-item pair, or by estimating the probability that a user will like an item. Extensive research on recommendation systems over the last few decades has led to the development of two key approaches: content-based and collaborative filtering. Content-based approach focuses on the user's preferences, analyzing the content of items that the user has previously interacted with in order to recommend similar items. Collaborative filtering, on the other hand, uses the preferences of other users to recommend items to the user [115].

Fig. 2.1 provides a overview of the user-item matrix, where the elements of matrix are the rating of m-th user for n-th item. A rating r_{ui} suggests user u's inclination towards item i, with higher value implying a more intense inclination [86]. Ratings may range

	Item 1	Item 2	Item 3	...	Item n
User 1	2	3	?	...	5
User 2	?	4	3	...	?
User 3	3	2	?	...	3
...	...	...	...	...	...
User m	1	?	5	...	4

Fig. 2.1 User-item matrix

from 1 (star) representing a lack of interest to 5 (stars) symbolizing a great deal of interest. Most of the time, the great majority of ratings remain unknown. For instance, Netflix data shows that the majority of possible ratings are absent since a user usually rate a small selection of movies.

This matrix is an important tool for analyzing user behavior, as it allows us to better understand the preferences and interests of the users. By using this matrix, we can also identify potential correlations between users and items, enabling us to recommend items that are likely to be of interest to the user.

2.1.1 Content-based filtering

Content-based filtering (CBF) uses user- or item-specified attributes to form the basis of comparison, which will be then to determine relevance. By leveraging behaviour history, CBF are able to identify and recommend items that are likely to be of interest to the users [72, 170]. Specifically, content-based filtering examines a collection of items and/or descriptions that have been evaluated by a user, and builds a representation of the user's preferences. The recommendation result is a correlation that reflects the user's degree of preference for the item. The idea behind content-based filtering is that if a user likes an item, they are likely to like other items with similar characteristics. By focusing on the characteristics of items, content-based filtering can provide personalized recommendations that are tailored to a user's individual interests.

Three key components of CBF are summarized as follows:

- Content analyzer: When data presents in an unstructured format (e.g. text), a pre-processing step is employed to obtain meaningful, structured information. The analyzer convert inputs (e.g. documents, web pages, news, product descriptions, etc.) into a format that is compatible with the subsequent steps in the process.
- Profile learner: By leveraging description or attributes from items the user has interacted with, profile learner develops a profile that incorporates the user's interests and preferences.
- Filtering component: The recommendations are given by finding the similar items of items users liked in the past. In particular, This component utilizes the user profile to recommend relevant items.

In summary, the content-based approach involves assessing the attributes of items that the target user has given a rating to and then suggesting new items having these characteristics to the target user. On the one hand, a content-based approach has the ability to suggest items that have yet to be rated by any individual, making it a suitable solution for the cold-start problem in recommendation systems. On the other hand, a content-based approach deeply relies on available information, resulting in two potential drawbacks: limited content analysis or over-specialization. Limited content analysis refers to limitations in the content or the amount of information available. In such cases, the analysis will only be as accurate as the content available, meaning it may be too superficial or inaccurate. Over-specialization occurs when a content-based approach becomes overly focused on a single area, and as a result, fails to capture the full scope of the data.

2.1.2 Collaborative filtering

Collaborative filtering (CF)uses the collective knowledge of a group of users to make informed recommendations. It establishes connections between distinct elements, such as items and users, to create personalized recommendations.CF-based approaches can be divided into two classes: Neighborhood-based CF and model-based CF.Neighborhood techniques, which include user-based CF and item-based CF, focus on the relationships between items or, in the opposite case, users. Specifically, the user-based CF approach predicts the rating r_{ui} that the user u would likely give to item i by examining the ratings of the user's similar neighbors on that item. Rather than evaluating the similarity between users like in user-based CF, item-based CF looks at the similarity between items, and then suggests to the target user those items that are similar to what the active user has previously liked [83, 97].

Model-based CF builds models using the user-item rating matrix's known data to predict unknown information. Various classification models have been tailored to CF situations, such as decision tree, Bayesian classifier, support vector machine, neural network, etc. [3, 34]. Different from traditional techniques, model-based CF treat recommendation task as matrix factorization problem. Researchers have consistently favored and paid attention to matrix factorization due to its its capacity to address sparse issues on a large scale. Fig. 2.2 provides a concise overview of different mechanisms of content-based and collaborative filtering.

For every user u, the set of items they have rated, denoted by $R(u)$, includes all the items they have provided ratings for. The latent factor models approach to collaborative filtering is designed to uncover hidden characteristics that explain why certain ratings have been given. These models include, but not limited to, pLSA [20], neural networks [63], Latent Dirichlet Allocation [85], and techniques that are derived from the decomposition of the user-item ratings matrix (also known as SVD-based models).

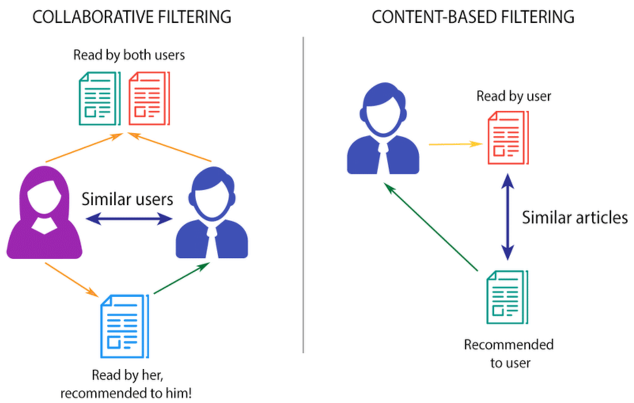

Fig. 2.2 Content-based filtering vs Collaborative filtering

2.1.3 Hybrid approach

The hybrid filtering technique has been developed to tackle some of the shortages encountered with the existed filtering strategies, such as the cold start issue, overspecialization issue, and sparsity problem [15].The implementation of hybrid filtering is also intended to enhance the accuracy and effectiveness of the recommendation process.

Recent studies [10, 2] have demonstrated that a combined approach could be more advantageous in certain situations.The primary objective of the hybrid approach is to combine collaborative filtering and content-based filtering in order to enhance the precision of the recommendations.Different strategies can be employed to incorporate hybrid approaches.

- Implement both collaborative and content-based approaches separately and then combine their outcomes.
- Incorporate some content-related qualities into a collaborative approach.
- Integrate elements of collaboration into a content-based approach and build a unified model that brings together both content-based and collaborative elements.

The sparsity and cold start issues encountered in recommender systems can be addressed by utilizing these techniques.Hybrid recommender can also be found in Netflix.They suggest films to viewers by studying the movie-viewing tendencies of similar audiences (collaborative filtering) and by recommending titles that have similar characteristics to films that the viewer has liked in the past (content-based filtering).

Burke [10] provided a categorization of Hybrid Recommendation Systems, which he divided into eight distinct classes.

- Weighted: Various recommendation component scores are combined.This class combines results from all factors by adding them together.
- Switching: The recommendation components system selects a specific component from the available options and applies it.
- Integrate elements of collaboration into a content-based approach and build a unified model that brings together both content-based and collaborative elements.
- Mixed: Various recommender systems will be presented in tandem with their respective recommendations.This class focuses on combining several ranked lists and presenting them as one.
- Feature Combination: This class has two distinct recommendation components, namely, contributing and actual recommender, which contribute to feature combination. The effectiveness of a real-time recommender system relies on the data provided by contributors.The contributor incorporates aspects from one source into the other source's components.
- Feature Augmentation: This class is akin to feature combination hybrids, however, the contributor provides a distinctive quality that sets it apart. It has a greater degree of flexibility than the feature combination approach.

- Cascade:Assign each recommender a priority, and if two higher-priority recommenders are in conflict, the lower-priority one will be used to decide the outcome.
- Meta-level: At the meta-level, there are both contributing and actual recommenders, yet the former completely replaces the data of the latter.

2.2 Multi-Objective Optimization

2.2.1 Introduction

In real life, individuals often encounter scenarios where multiple goals need to be considered at the same time, which are referred to as multi-objective problems (MOPs). For example, finding an optimal balance between nutritional aspects, harmony, and coverage of available ingredients in menus. MOPs refer to minimising or maximising multiple objectives that are conflicting, with the improvement of one objective leading to the degradation of others. When there are more than three objectives in the specified problems, the tasks are defined as many-objective problems (MaOPs) [88].

2.2.2 Multiobjective optimization

Multi-objective optimization (MOO) problems gives rise to a set of optimal solutions (known as the Pareto-optimal solutions), instead of a single optimal solution. None of the optimal solutions can claim to be better than any other with respect to all objective functions. MOO brings a number of challenges that need be addressed, which highlights the need for effective algorithms that can handle the growing number of objectives. Some of these successful methodologies include Strength Pareto Evolutionary Algorithm (SPEA) [188] , SPEA2 [187], Non-dominated Sorting Genetic Algorithm (NSGA) [148], NSGA-II [26] and Pareto Archived Evolution Strategy (PAES) [84].

Without loss of generality, a simple multi-objective problem can be formulated as:

$$\begin{aligned} \min F(x) = (f_1(x), f_2(x), \ldots f_m(x))^T \\ x \in X \subset \mathbb{R}^n \end{aligned} \tag{2.1}$$

where $x = (x_1, \ldots, x_n)$ is a vector of n decision variables and X is an n-dimensional decision space. m is the number of objectives to be optimized. When $m \geq 4$, the problem are referred to as many-objective optimization problems. The optimal solutions are are also known as non-dominated solutions. In a minimization problem, a solution x is considered non-dominated in comparison to another solution x^* when no objective value of x^* is less than x and at least one objective value of x^* is greater than x.

One of the most popular algorithms in literature is the NSGA-II [26]. It is often used as a baseline algorithm for comparison with new algorithms. The NSGA-II is a computationally fast and elitist MOEA based on a non-dominated sorting approach. It also uses an explicit diversity-preserving mechanism to obtain a set of well-spread Pareto-optimal solutions. The NSGA-II was initially tested on problems with smaller number of objectives, but over the years it has shown to be successful in solving problems with many objectives as well.

A number of NSGA-II improvements have been proposed over the years to make the algorithm more efficient in handling a larger number of objectives. ε-NSGA-II combines NSGA-II with an ε-dominance archive, adaptive population sizing and time continuation [81]. This algorithm has also been widely used for many different real world many-objective problems.

Other classical methods to tackle the MaOP problem, are ε-MOEA, which is a steady-state MOEA that exploits the benefits of an ε-dominance archive [68]. MOEA/D is another algorithm which has shown success with many-objective optimization. It uses a decomposition method to decompose the given problem into a number of scalar optimization problems. These sub-problems are then simultaneously optimized using an evolutionary algorithm. The MOEA/D has been used for comparison in various recent studies, making it a benchmark algorithm for many-objective optimization [189]. Deb and Jain [27] proposed the NSGA-III which uses a reference point based approach for many-objective optimization, showed superior performance in comparison to methods such as the MOEA/D and NSGA-II.

2.2.3 MOO for recommendation systems

In recent years, multi-objective optimization techniques have been successfully applied in the field of recommender systems. In contrast to traditional recommendation models, which often aim for a single goal, such as minimizing prediction errors or improving recommendation accuracy, multi-objective recommender systems (MORS) are often able to take into account multiple objectives to provide an optimal solution to a given task. Several studies [53, 32] have been proposed to develop MORS based on different scenarios.

Most of existing research for MORS consider recommendation quality metrics,such as novelty, diversity, serendipity and popularity, as multiple objectives to optimize. For example, [53] proposed a multi-objective optimization approach to collaborative filtering that considers both accuracy and diversity. Similarly, [32] proposed a multi-objective optimization approach to recommender systems that considers both accuracy and coverage. Other work, such as [190, 122, 14, 12], included coverage as one of their objectives. Xie et al. [171] proposed a new Personalized Approximate Pareto-Efficient Recommendation model with two objectives, click-through rate and dwell time. In contrast, Wang et al. [165] proposed a multi-objective framework for long-tail items recommendation with accuracy and diversity as two objectives to optimize. Despite the fact that many MORSs attempt to enhance the quality of recommendations through the use of various metrics, the lack of uniform definitions for these metrics creates a challenge when comparing the effectiveness of different recommendation systems. For instance, some research use prediction errors to indicate recommendation accuracy, while others use other metrics such as click-through rate or dwell time [122]. Despite these challenges, multi-objective optimization approaches have shown promising results in improving recommendation quality by considering multiple objectives simultaneously.

In addition to the quality metrics, MOO can be used to model conflicts between individual choices and collective satisfaction. In their research, Xiao et al. [172] investigated group satisfaction, social relationship density (i.e., the degree of social proximity between group members), and group fairness. They utilized a variance-based fairness metric in addition to four distinct group fairness indices. Multi-stakeholder recommendation models (MOOs) provide suggestions by taking into account the viewpoints of numerous stakeholders, such as users, sellers, merchants, job-seekers, and recruiters. MOOs are intended to achieve a balance among various stakeholders and execute a user matching procedure to propose a user to the target user. Reciprocal recommendation models are based on the notion of bidirectional user preference and perform a process of user-matching to recommend a user to the target user, such as dating [191] or job-seeking [143].

2.3 Deep Learning for Recommendation Systems

2.3.1 Introduction

In recent years, various deep-based recommender systems have been proposed, transforming the designs of recommender systems and introducing new performance-enhancing possibilities. The wide range of neural network architectures, such as

Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), have enabled the development of sophisticated deep-based recommender systems that can improve the performance of existing recommender systems. One of the most appealing characteristics of neural networks is that they are (1) end-to-end differentiable and (2) give input-specific inductive biases. Therefore, if the model can utilise an inherent structure, then deep neural networks should be beneficial. Convolutional Neural Networks (CNNs) and RNNs, for instance, have utilised the intrinsic structure of vision (and/or human language) for decades. Likewise, the sequential structure of session or click-logs is well-suited for the inductive biases offered by recurrent/convolutional models [61, 153, 166].

Deep learning has revolutionized the way in which recommendation systems can provide personalized recommendations for each user. By leveraging the power of artificial intelligence, deep learning algorithms can analyze large amounts of data and use it to learn and identify patterns that are specific to each user. This allows for a much more accurate and personalized recommendation system, as the algorithm is able to identify each user's individual preferences. With automated personalization, users can receive more accurate and personalized recommendations that are tailored to their individual needs.

Many online websites and mobile applications rely on recommender systems to enhance the user experience and promote sales/services [16, 21, 117]. For example, eighty percent of movies watched on Netflix were based on recommendations [55], while sixty percent of video clicks on YouTube were based on home page recommendations [16].

2.3.2 Deep learning techniques

Programming computers to learn from data is both an art and a science known as Machine Learning. For example, spam filter utilizes machine learning to identify and flag potential spam emails, which are distinguished from regular emails by examples that have been previously marked. Deep Learning is a subset of machine learning that uses neural networks to create models that can learn from large amounts of data [100]. There are three main types of deep learning-based systems: supervised learning, unsupervised learning, and reinforcement learning [28]. Supervised learning uses labeled data to learn a mapping between inputs and outputs, while unsupervised learning uses unlabeled data to discover hidden structures and features in data. Reinforcement learning uses rewards to teach machines to take the best action in a given situation. Each of these approaches has its own advantages and disadvantages, and can be used in a variety of applications.

In supervised learning, the input data set you provide to the algorithm contains the expected solutions, referred to as labels. A common type of supervised learning is categorization task [119]. An illustration of this can be seen in the spam filter: it is exposed to various emails with a specified label (spam or ham) and it must learn how to correctly categorize new emails. Another common task is to estimate a numerical target, for example the cost of an car, based on a set of descriptors (mileage, age, make, etc.) called predictors.The task described is referred to as regression.

In unsupervised learning, the training data does not have any labels associated with it. This means that the algorithm does not have any prior knowledge of the data and must learn to recognize patterns and structure from the data itself [77]. This is in contrast to supervised learning, where the algorithm is given labels to learn from. Unsupervised learning is a powerful tool for making sense of complex data and can be used to identify patterns, clusters, or outliers in the data.

Reinforcement Learning is different from the above two methods.The agent, referred to as the learning system in this instance, is capable of monitoring the environment, taking action, and receiving rewards [93].It then figure out independently what is the most efficient plan, referred to as a policy, to maximize its gains in the long run.A policy outlines what course of action the agent must take when faced with a particular scenario.

Despite machine learning being an effective tool for developing predictive models from data, it also presents some unique challenges. One of the main challenges is the need for large amounts of training data to achieve accurate predictions. Additionally, the data must be clean and properly formatted to be used effectively. Furthermore, there are often complex relationships between the data points which can be difficult to model accurately.

2.3.3 Deep learning for recommendation systems

Recent years have seen an increase in the number of businesses employing deep learning to improve the quality of their recommendations. Covington et al. [21] demonstrated a recommendation method for YouTube videos based on a deep neural network. Cheng et al. [16] presented a comprehensive and deep model for an App recommender system for Google Play. Shumpei et al. [117] introduced a Yahoo News RNN-based news recommender system.

Regarding interaction-only sorting (i.e., matrix completion or collaborative ranking issue), the essential point presented here is that deep neural networks are justifiable when there is a great deal of complexity or a big number of training examples. In [63], the authors approximated the interaction function using an MLP and demonstrated significant performance improvements over conventional approaches such as MF. Moreover, Tay et al. [159] have reported that conventional machine learning models, such as BPR, and CML, demonstrate favorable performance when trained using momentum-based gradient descent on interaction-only data.

One of the major challenges with deep learning models in recommendation systems is their lack of interpretability. While these models can provide accurate recommendations, it can be difficult to understand how they arrived at those recommendations. This can be particularly problematic when making decisions in sensitive or high-stakes situations. In order to address this issue, researchers have proposed various techniques for interpreting deep learning models, such as layer-wise relevance propagation (LRP) [8], attention mechanisms [135], and explanation-based learning [102]. However, more research is needed to improve the interpretability of deep learning models in recommendation systems.

Another challenge in recommendation systems is how to better capture the dynamic relationship between users and items. Traditional recommendation systems often rely on static user-item interactions, which may not accurately reflect the changing preferences and behaviors of users over time. Deep learning models offer the potential to capture these dynamic relationships, but doing so can be difficult due to the high dimensionality and sparsity of recommendation data. Researchers have proposed various solutions to this problem, such as incorporating temporal information into the model [61] and using recurrent neural networks to model sequential data [62]. Additionally, deep learning models can also benefit from incorporating contextual information, such as user demographics or item attributes, to better capture the nuanced relationships between users and items.

Chapter 3

Many-Objective Optimization for Food Recommendation Systems

3.1 Motivation

Due to the ever-increasing amount of various information provided by the internet, recommendation systems are now used in a large number of fields as efficient tools to get rid of information overload. The content-based, collaborative-based and hybrid methods are the three classical recommendation techniques, whereas not all real-world problems (e.g. the food recommendation problem) can be best addressed by such classical recommendation techniques. This chapter is devoted to solving the food recommendation problem based on many-objective optimization (MaOO). A novel recommendation approach is proposed by transforming the original recommendation problem into an MaOO one that contains four different objectives, i.e., the user preferences, nutritional values, dietary diversity, and user diet patterns. The experimental results demonstrate that the designed recommendation approach provides a more balanced way of recommending food than the classical recommendation methods that only consider individuals' food preferences.

Recommendation systems (RSs) employ users' history data records to predict their preference, and have been widely used in fields like e-commerce, movie, and music recommendation to help people overcome information overload [178, 177, 4, 179]. Due to the growing attention to a healthy and balanced diet, food recommendation has now become more and more popular among people worldwide. It has been shown by researchers that a long-term unhealthy diet exposes people's health to unaware risks [35], e.g. the development of certain chronic diseases such as cancer, diabetes and obesity [39]. Given the importance of a balanced and healthy diet, there is an urgent need to use recommendation techniques to assist people in selecting scientific yet personalized food plans.

Generally speaking, food RSs utilize users' food consumption data to predict their food preferences and recommend healthier substitutes to such preferences. It has been verified that traditional recommendation techniques (e.g. the content-based, collaborative-based and hybrid methods) perform well in analyzing rectangular data sets [80]. Rectangular data sets are structured data arranged in rows and columns, where each row corresponds to a user and each column represents a rating, or vice versa. When it comes to non-rectangular food-related data sets such as meals, restaurants and food intake, these traditional recommendation techniques fail to provide satisfactory suggestions on a balanced and nutritional diet. For instance, a meal may consist of several food items, each with their own nutritional values, and a restaurant may have different types of cuisines, locations, and price ranges. Such data sets may require more sophisticated approaches to analyze and recommend items, since traditional recommendation techniques that rely on tabular data may not capture the complexity and interrelatedness of the data.

In order to solve this problem, the multi-objective optimization (MOO) algorithms have been introduced to the food recommendation field. These algorithms aim to optimize multiple objectives, such as user preferences and food nutritional values, to provide more personalized and balanced recommendations. However, it should be noted that most existing MOO-based recommendation studies in the food domain have only considered a limited number of objectives, often leading to sub-optimal recommendation plans. Taking into account the fact that many other objectives (e.g. food diversity and user diet patterns) also pose significant impacts on health-related recommendation, it would be quite interesting to investigate how such objectives could be integrated into the MOO problem so as to provide more scientific and efficient recommendation. This seems to be a nontrivial task due to the great difficulty in considering so many food-related objectives simultaneously in one MOO model, which can bring high computation costs and great visualization difficulties [144, 180].

In this chapter, a novel MaOO-based approach is developed to provide a balanced and systematic way of dealing with food recommendation tasks. An MaOO model is proposed by considering four crucial objectives related to user preference, user diet pattern, food nutritional values, and food diversity. Three Pareto-based algorithms are applied to solve the given recommendation task, and the experimental results demonstrate the effectiveness of our model in food recommendation.

The main contributions of this chapter can be summarized as follows: 1) a new food recommendation problem is considered that targets at supplying users with a scientific yet personalized diet, where four different food related objectives are required to be simultaneously optimized; 2) a novel MaOO based recommendation framework is developed to solve the proposed recommendation task, where three MaOO approaches are delicately combined to convert the original recommendation task into an MaOO problem; and 3) a series of experiments based on real-world data sets are conducted to verify the effectiveness of the proposed MaOO based recommendation framework.

The rest of the chapter is organized as follows: Section 3.2 presents the related work about traditional food recommendation methods. Section 3.3 develops an MaOO model for food recommendation. Section 3.4 discusses the experimental results and the corresponding metrics chosen for algorithm evaluation. Section 3.5 presents some conclusions and future directions.

3.2 Related work

As an efficient tool in helping users coping with overwhelming food information, the food RS is able to employ recommendation techniques to 1) learn user requirements from massive historical user data (e.g. recipe ratings, browsing history, and implicit feedback); 2) build a disease- and nutrition-oriented food recommendation model; and 3) provide users with personalized and healthy diet. In the sequel, a comprehensive introduction to typical food recommendation techniques and their application status is provided.

Traditional recommendation algorithms (e.g. the content-based, collaborative-based, hybrid and collaborative filtering methods) are featured with machine learning approaches (including the logistic regression, random forest and support vector machine techniques), and are often applied to deal with rectangular data sets for food recommendation[42]. Note that food recommendation, as a special recommendation filed, is different from its counterparts such as movie or e-commerce recommendation [154] and the difference can be summarized as follows.

The first difference is about rating. It is known that rating has a dominant effect on algorithm outputs in movie or e-commerce recommendation, whereas rating only has a small influence on the algorithm outputs of food recommendation. In the context of movie or e-commerce recommendation systems, the ratings provided by users have a significant impact on the algorithm outputs as these systems heavily rely on user feedback to generate recommendations and often prioritize highly rated items over others. However, the influence of ratings in the case of food recommendation systems is relatively small since food preferences are highly subjective and can vary widely among individuals. It is challenging for a rating-based system to accurately capture the nuances of each user's tastes, and thus, food recommendation systems rely on a combination of other factors such as ingredient compatibility and past purchase history to generate personalized recommendations [112].

The second difference is about information. Preference learning is a complex and important task in food recommendation that requires more context information in comparison with general recommendation tasks [82]. The third difference is about feedback. Unlike many other recommendation tasks (e.g. movie recommendation), the feedback from users in food recommendation might not always result in satisfactory recommendation. To be specific, in food recommendation, feedback from users only reflects their own taste preferences, and might not always contribute to a healthy diet [112].

So far, very little work has been done on food recommendation under real-world settings [106]. This is due to the reason that the food intake data in real-world scenarios typically appear in a non-rectangular form. As a result, it is hard for traditional recommendation techniques to process such data. In addition, the rich contextual information contained in the real-world food data set is difficult to be captured by traditional recommendation techniques. To solve these problems, in recent years, the MaOO method has become quite popular in the field of food recommendation as the MaOO is capable of converting food recommendation problems into MaOO ones, which overcomes the drawback of traditional recommendation techniques.

Regarding MaOO-based health- or nutrition-oriented food recommendation, tailored objectives (closely related to research backgrounds) are required to be added to the MaOO model. For example, four objectives (i.e. the food preferences, preparation time of meals, budgets, and availability from cooked dishes) have been firstly formulated in [161], and the well-known many-objective evolutionary algorithm has then been used to solve the diet recommendation problem. A food package suggestion has been presented in [164] based on real-world restaurants, where the number of dishes, diversity of dish categories and popularity of dishes have been considered as three objectives that need to be maximized. In [160], tailored objectives have been constructed for recommending healthy meal plans based on the user age and vulnerable health background in real clinic institutions.

It is worth mentioning that food recommendation is often accompanied by complex research backgrounds, and this undoubtedly brings great challenges to the design of MaOO-based food recommendation approaches. One way to cope with such challenges is to come up with more scenario-related objectives. The other way is to explore more appropriate MaOO algorithms that cast deeper insights into food recommendation scenarios. Although the aforementioned two ways perform well in tackling challenges underlying food recommendation, they both have built themselves on classical MaOO algorithms and have ignored the fact that, food recommendation has its uniqueness and restrictions (e.g. the age, location, environmental information, allergies and food beliefs) [82]. This motivates us to investigate more specialized MaOO algorithms that target at supplying users with better food recommendation plans.

3.3 A many-objective optimization model for food recommendation

3.3.1 Data Collection and Preparation

A free online health and fitness mobile app called MyFitnessPal (MFP) is used in this study, which records users' daily food intake and counts calories consumed [1]. The MFP data set provides 1.9 million records of meals recorded by 9.8K MyFitnessPal users from September 2014 to April 2015 on 71K food items. Furthermore, the MFP provides an Application Programming Interface (API) that enables developers to access data from the application [37]. The information can be retrieved includes the names of the food items consumed, the serving sizes, and the nutritional values of each item. To retrieve the data from the MFP application, HTTP requests are sent to specific endpoints with parameters such as user ID and date. The API would then return a JavaScript Object Notation (JSON) response containing the requested data. The nutritional information provided by the MFP API includes a wide range of macronutrients and micronutrients, including calories, protein, fat, and carbohydrates. This information can help to calculate user's nutrient intake.

Table 3.1 MyFitnessPal Data Set.

user_id	date	meal_sequence	food_ids
1	2014.09.14	1	1,2,3,4,5,6
4	2014.11.14	2	12,3,4,3
5	2015.01.14	4	9,5,9,2
173	2015.02.03	3	4,7,6,8,69
175	2015.03.14	1	2,12,42,6,9

Table 5.1 provides five examples of the MFP data set. The user_id and date represents user identifiers and record time of this entry, respectively. The meal_sequence indicates the order of the meals on a given day, e.g., meal_sequence = 1 indicates the day's first meal. The food_ids records food entries that users have consumed.

Table 3.2 MyFitnessPal Food Data Set.

id	item
1	fruit_tropical_banana
2	dessert_confectionery_chocolate
3	staple_wheat_spaghetti
4	meat_sausage_hot_dog, staple_wheat_bun
5	bean_legume_legume_bean

Table 5.4 contains five examples of food entries for each food_id list. Each food_id is composed of a triplet of meal type, food types, and specific food separated by

underscores. The MFP API is used to retrieve nutritional information for each food item.

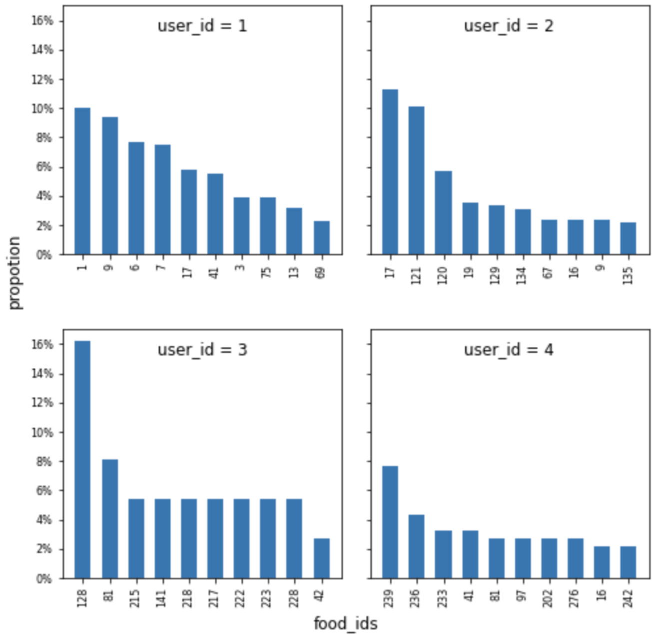

Fig. 3.1 Histograms of four users.

In Fig. 3.1, we analyze the dietary frequency of four randomly users from the MFP data set. The x-axis displays the food_id, and the y-axis shows the proportion of total food consumption represented by each food. It is clear that users 2 and 3 possess a strong preference for certain foods, while users 1 and 4 exhibit less inclination for certain foods, but still prefer certain foods as their favorites. We can conclude from the histogram that users tend to develop a stable preference for food.

3.3.2 Problem formulation

User preference

User preferences refer to the attitudes and preferences that individuals have toward foods [42]. It is essential to learn the user's preferences for food, since users tend to expect food that satisfies their preferences. The Positive Point-wise Mutual Information

(PPMI) is used in this chapter as a measure of correlation between two food items in the data set, as well as a qualitative measurement for evaluating food preferences [7]. We compute the correlation matrix using PPMI for all the foods in the MFP data set.

Objective 1: Maximize user preference

$$\mathrm{PPMI}(f_i, c_i) = \max\left(\log_2 \frac{P(f_i, c_i)}{P(f_i)P(c_i)}, 0\right) \tag{3.1}$$

where f_i and c_i denote the i-th food item in Table 3.2 and the i-th food context in Table 3.1, respectively. If f_i and c_i are not correlated, $P(f_i, c_i)$ is equal to $P(f_i)P(c_i)$. $P(f_i)P(c_i)$ is greater than $P(f_i, c_i)$ when f_i and c_i are correlated. The higher the PPMI, the larger the correlation between the f_i and c_i.

The PPMI is chosen as a metric because it performs better in a context-related scenario by comparing to other similarity measurements. As presented in Table 3.1, the food_id vectors' lengths are time-varying. Other widely applied similarity metrics, such as Pearson correlation coefficient and cosine similarity, are not suitable for the data set due to the following reasons: 1) The Pearson correlation coefficient (PCC) is a measure of linear correlations between two sets of data, which is generally used in recommendation areas where rating matrices are available; 2) The cosine similarity is a measure of similarity between two non-zero vectors of an inner product space, and the length of the vectors is required to be the same. Thus, in this chapter, the PPMI is chosen as the measure to assess users' food preference learning.

Table 3.3 PPMI Matrix.

food_id	1	2	3	4	5	6	7	8
1	0.0	0.0	2.55	2.06	2.25	2.45	2.50	2.46
2	0.0	0.0	0.00	2.92	3.15	2.74	2.75	2.45
3	0.0	0.0	0.00	0.00	2.72	2.08	2.11	2.48
4	0.0	0.0	0.00	0.00	0.00	2.67	2.46	2.08

Table 5.3 shows the PPMI scores for all food items. In the PPMI matrix, each row represents a food item $f \in V_f$ and each column represents a context $c \in V_c$, where V_f and V_c are the sets of food items and their contexts, respectively. Each cell M_{ij} represents the correlation between the food item f_i and the context c_i indicated by the PPMI in Equation (5.1). PPMI matrix is also used in the nutrition section to find healthier substitutes.

Nutrition

Malnutrition is associated with symptoms such as fatigue, dizziness, and even diseases [149]. Therefore, balanced nutrition intake is necessary for the users' health. The World Health Organization (WHO) published a document entitled Diet, nutrition, and prevention of chronic diseases in 2002, where unbalanced food intake is identified as the primary cause of chronic metabolic diseases like obesity [116]. Table 3.4 provides information regarding the nutritional intake of users according to WHO guidelines.

Table 3.4 provides the population nutrition intake recommendation for prevention of diet-related chronic diseases. The recommendation's percentages may vary depending on the intake of a particular population.

Table 3.5 contains the nutrient value of each food in the MFP food data set and is used to calculate the proportion of each nutrient in the food.

To quantify the nutritional value of each food, we calculate nutrition scores from the nutrition indexes of the three major nutrients: protein, carbohydrate, and fat. We set a default value of zero for each nutrient. Using protein as an example, if the calculated intake falls outside the recommended range, we determine the absolute difference compared to the lower and upper bounds of the suggested range. Similar results can be obtained for carbohydrates and fats.

Table 3.4 WHO Daily Intake Standard.

Ranges of population nutrient intake goals	
Dietary factor	Goal(% of total energy, unless otherwise stated)
Total fat	15-30%
Saturated fatty acids	10%
Polyunsaturated fatty acids (PUFAs)	6-10%
n-6 Polyunsaturated fatty acids (PUFAs)	5-8%
n-3 Polyunsaturated fatty acids (PUFAs)	1-2%
Trans fatty acids	1%
Monounsaturated fatty acids (MUFAs)	By difference
Total carbohydrate	55-75%
Free sugars	10%
Protein	10-15%
Cholesterol	300 mg per day
Sodium chloride (sodium)	5g per day (2g per day)
Fruits and vegetables	400g per day
Total dietary fibre	From foods
Non-starch polysaccharides (NSP)	From foods

Table 3.5 Table of Nutrients.

food_id	total_calories	fat_calories	carbohydrates_calories	sugar_calories	protein_calories
1	150.0	72.00	48.00	44.00	32.00
2	627.0	263.97	137.76	52.92	189.16
3	410.0	117.00	248.00	4.00	88.00
4	510.0	189.00	104.00	40.00	176.00
5	270.0	54.00	12.00	4.00	80.00

Objective 2: Maximize S_i

$$
\begin{aligned}
S_i = &|sp_i - 0.1| + |sp_i - 0.15| + |sc_i - 0.55| \\
&+ |sc_i - 0.75| + |sf_i - 0.15| + |sf_i - 0.3|
\end{aligned}
\tag{3.2}
$$

where S_i stands for nutrition score of the i-th food item, and sp_i, sc_i and sf_i denote the corresponding calculated protein, carbohydrate, and fat percentage, respectively.

Food Diversity

Users often overlook the importance of food diversity, which compensates for nutritional deficiencies to a large extent. For example, 97% of Americans' fibre intake don't reach the daily minimum [5]. In this regard, a necessary recommendation strategy is employed to encourage users to discover more heterogeneous foods that provide a nutritional supplement of fiber, minerals and unsaturated fats. The Simpson index is used as the diversity metric here, which is expressed as follows.

Objective 3: Maximize Diversity

$$
D = 1 - \sum_{i=1}^{n} P_i^2 \tag{3.3}
$$

where n is the number of food items, P_i indicates the probability for two food items to be chosen as the same food items of one user's food consumption data. P_i^2 is the random joint probability of two food items. This diversity index can reflect whether a user's food intake is heterogeneous or not in a period.

User Diet Pattern

An individual's diet pattern is a dynamic feature that reflects their eagerness for specific types of food at specific times, which has a non-negligible impact on the acceptance of recommendations. User diet patterns change over time, resulting in users having different daily food intakes [118].

To measure changes in diet patterns over time, we chose Dynamic Time Warping (DTW) as an indicator, which is originally designed for comparing two time series of different lengths during the same time-period [145]. The primary reason for choosing DTW is that it can measure the similarity of two sequences of different lengths [150].

Objective 4: Maximize DTW

$$\begin{aligned} \mathrm{DTW}(i,j) = -\mathrm{Dist}(i,j) + \min[&\mathrm{DTW}(i-1,j), \\ &\mathrm{DTW}(i,j-1), \mathrm{DTW}(i-1,j-1)] \end{aligned} \tag{3.4}$$

Given two food vectors X and Y, their lengths are $|X|$ and $|Y|$, respectively. The wrapping path can be formulated as $W = w_1, w_2, \ldots, w_k$, satisfying $\max(|X|,|Y|) <= K <= |X|+|Y|$, where $w_k = (i, j)$ is a tuple of $|X|$ and $|Y|$'s coordinates, respectively. The wrapping path starts from $W_1 = (1,1)$ and ends at $W_k = (|X|,|Y|)$. It finally generates the shortest path between two distinct length vectors.

3.3.3 A many-objective optimization model

In MaOO, there are multiple objectives, typically over three. The complexity of MaOO increases rapidly with the increasing number of objectives, making it intractable in case of a large objective number [56]. In this chapter, an MaOO model is developed to provide a balanced and systematic way of dealing with food recommendation tasks. Four crucial objectives related to health, user preferences, user diet patterns, food nutritional values, and food diversity. Three representative MaOO algorithms are applied, and their performances evaluated. Our model is structured as follows:

Algorithm 3.1 describes the fundamental model structure. First, the initial population is formed by N randomly-generated individuals. Second, a fitness vector of the initial population is obtained, where each value represents fitness for each individual. Third, mating selection which includes mutation and crossover is performed to find the fittest individuals for the next generation. Finally, the environmental selection is implemented to keep the population sizes.

Algorithm 3.1 Main Algorithm

Require: P (population), N (population size)
$P \longleftarrow Initialize(P)$
while termination criterion not fulfilled **do** $Fitness\_calculation(P)$
$P' \longleftarrow Mating\_selection(P)$
$P \longleftarrow Environmental\_selection(P')$
end while
Return P

Fitness is an indicator of an individual's ability to adapt to their environment. Mating Selection aims to drive the population evolution towards the optimum by a series of biological reactions, such as mutation, crossover, and tournament selection. Algorithm 3.2 gives detailed steps of mating selection. First, mutation and crossover, which are characterized by gene recombination, create the potential of gene diversity. Second, tournament selection finds the fittest ones of the population to form the offspring population. Finally, the offspring population is fed into the MaOO problem.

Algorithm 3.2 Mating Selection

$P \longleftarrow Fitness\_calculation(P)$
$Mutation(P)$
$Crossover(P)$
$P' \longleftarrow Tournament\_selection(P)$
return P'

Environment selection is applied to obtain the best approximation of the Pareto-set. Only the dominant solution set of the individuals is chosen to enter the next selection. To maintain population sizes, external non-dominant sets are created. This process repeats until the termination criterion is satisfied.

Algorithm 3.3 Mating Selection

$P' \longleftarrow Mating\_selection(P)$
Initialize the external non-dominant set P'
Copy non-dominant members of P to P'
Remove dominant solutions within P'
Calculate the fitness value on four objectives for each individual in P and P'
Return P for initialization step

3.4 Experimental results and evaluation

For performance evaluation, three typical MaOO algorithms, i.e. the SPEA2 [76], NSGA-II [26], and SPEA2+SDE [89], are adopted for two different cases where the first case has three objectives and the other case has four objectives. Different Pareto optimal solutions are obtained and evaluated in every scenario.

3.4.1 Case I (three objectives)

In case I, three objectives are selected from the four objectives, and four different MaOO problems are formed. The experiment is conducted using the above stated MaOO algorithms, and the results obtained by the SPEA2+SDE are presented as an example. It is demonstrated by the experimental results that the Pareto optimal solutions vary under different combinations of objective functions and therefore, it is used as a reference of comparison in terms of trade-off patterns when adding the fourth objective.

Figs. 5.2-4.5 show that the Pareto-fronts optimization results of the three objectives, i.e. user preferences, nutrition scores and food diversity. Fig. 5.3 shows better convergence and diversity than Figs. 5.2, 4.4 and 4.5 for the fact that, the results in Fig. 5.3 are obtained by minimizing the distance of solutions to the optimal front and maximizing the distribution of solutions over the Pareto-front. The reason behind this is that

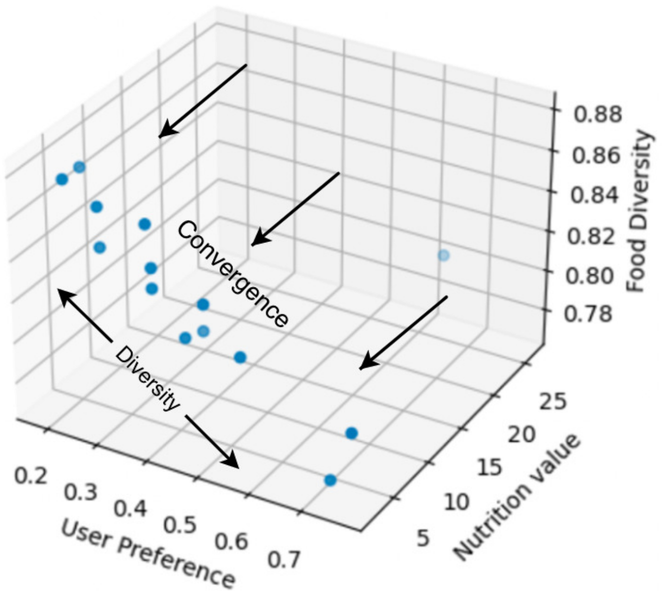

Fig. 3.2 Pareto-front of three objectives.

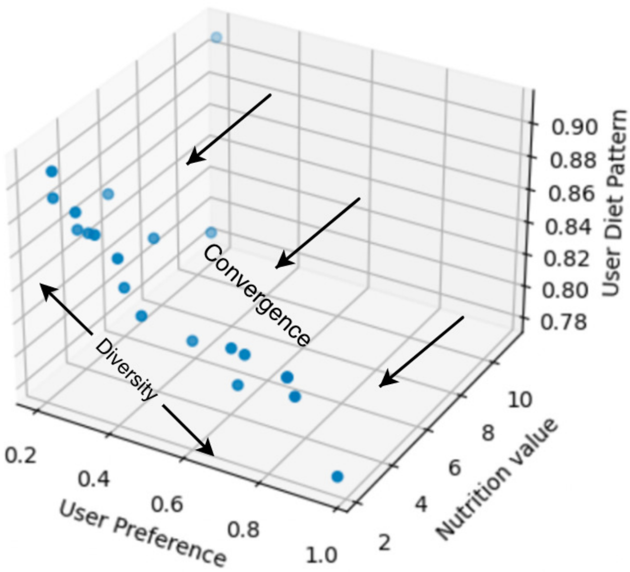

Fig. 3.3 Pareto-front of three objectives.

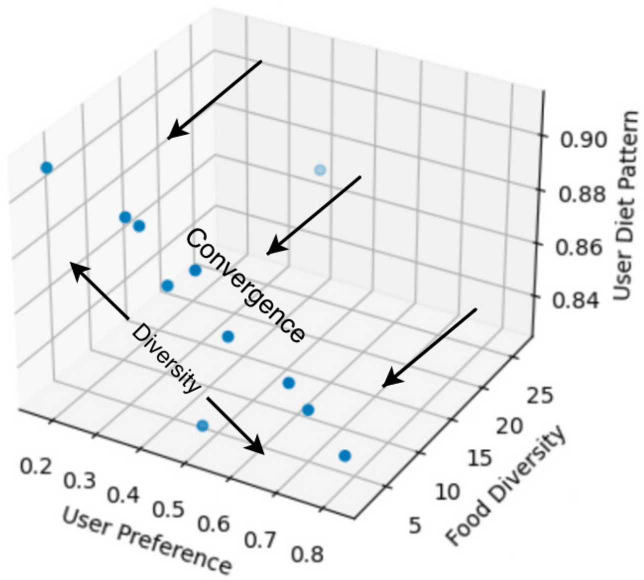

Fig. 3.4 Pareto-front of three objectives.

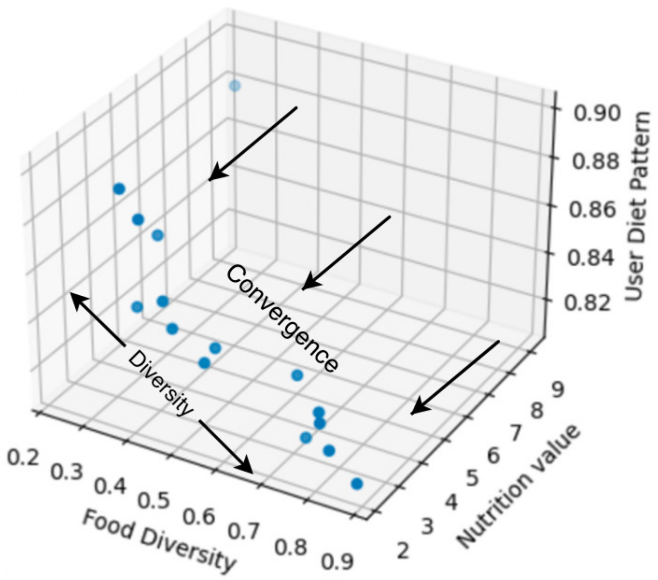

Fig. 3.5 Pareto-front of three objectives.

the information (about the user's dietary preferences, nutritional intake, and dietary patterns) is fully extracted from the data set in Fig. 5.3. Meanwhile, food diversity is limited by the users' dietary range of choices in Figs. 5.2,4.4 and 4.5. In summary, food diversity is an essential factor in guaranteeing individuals' health and should be considered and optimized simultaneously with other objectives.

3.4.2 Case II (Four objectives)

In Case II, user preference, nutrition values, food diversity and user diet patterns are optimized simultaneously, and the experimental results of the SPEA2+SDE-based methods are presented in Figs. 3.6-3.8. Three kinds of user group sizes are set for evaluating the convergence and diversity of these algorithms. It is found that Fig. 4.5 shows better convergence performance due to the density of the intersection of lines located on small range of the objective value.

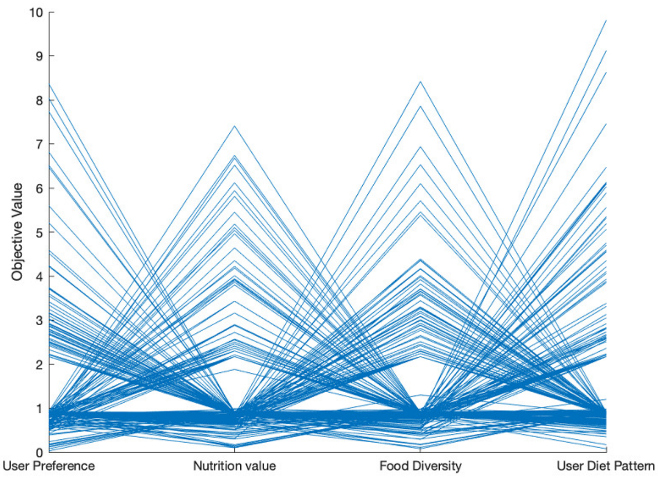

Fig. 3.6 Average of one user on four objectives.

3.4.3 Performance Comparison

Many metrics are put forward to evaluate the performance of MaOO algorithms, where convergence and diversity are the two most widely-used ones. Convergence evaluates

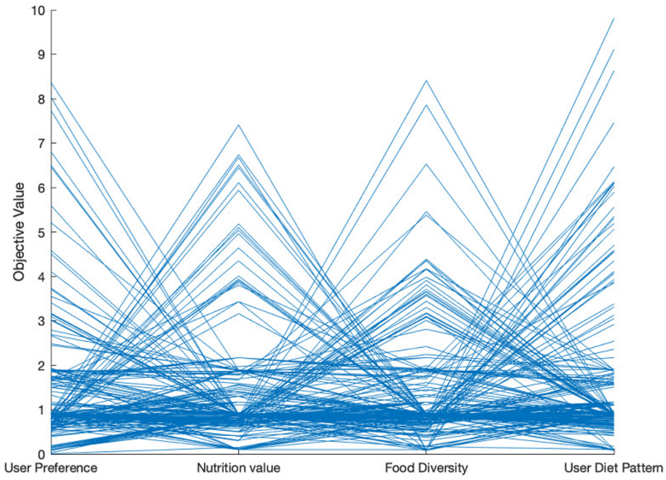

Fig. 3.7 Average of five user on four objectives.

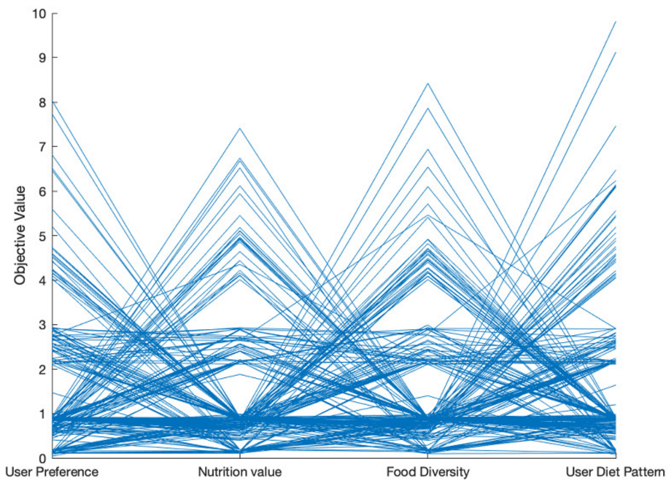

Fig. 3.8 Average of ten user on four objectives.

the approximation of the experiment results to the Pareto optimal front, while diversity is used to evaluate the distribution over the Pareto front [155]. In this chapter, the hypervolume is used as the performance metric and it has the advantage of being fully in line with Pareto dominance [151]. The hypervolume calculates solution sets by computing the intersection n-dimensional polytope between a set of solution points and an additional set of reference points. The volume of this polytope is referred to as the hypervolume. The hypervolume indicator is defined as follows:

$$H(\mathrm{S}) = \Lambda(\{q \in \mathbb{R}^d \mid \exists p \in \mathrm{S} : p \leq q \quad \text{and} \quad q \leq r\}) \tag{3.5}$$

Given a Pareto-front point set $S \subset \mathbb{R}^d$ and a reference point $r \in \mathbb{R}^d$, the hypervolume indicator of S is the measure of the Lebesgue measure region weakly dominated by S and bounded above by r.

A point $p \in \mathbb{R}^d$ is said to weakly dominate a point $q \in \mathbb{R}^d$ if $p_i \leq q_i$ for all $1 \leq i \leq d$, i.e. $p \leq q$. If $p \notin q$, then p is said to (strictly) dominate q, i.e. $p < q$. If $p_i < q_i$ for all $1 \leq i \leq d$, then p is said to strongly dominate q, i.e. $p \ll q$.

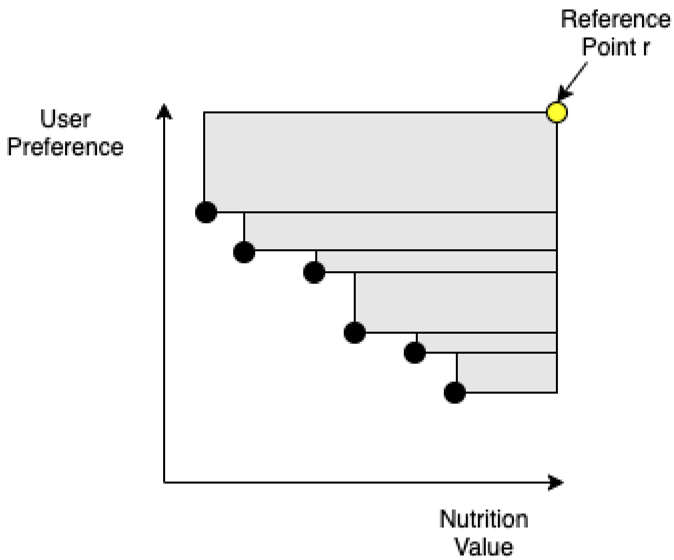

Fig. 3.9 Hypervolume illustration.

As it is difficult to illustrate the hypervolume indicator in four or more dimensions, Fig. 3.9 shows an example of hypervolume indicator calculation for two-objective optimization. As to the choice of reference point, it remains unclear how to decide the best reference point to use in a particular situation. Therefore, this chapter has chosen the reference point by 1.1 times the biggest value of every objective based on common practices [90]. The hypervolume indicator in two-objective optimization is defined as the area between each solution point and the reference point r, and the area size is used to compare the performance of different algorithms.

Table 3.6 Comparison of three MaOO algorithms' experimental results.

Model	Hypervolume indicator
SPEA2	0.59
NSGA-II	0.62
SPEA2+SDE	0.73

Table 3.6 presents a comparison of three MaOO algorithms according to the performance metrics. The hypervolume indicator performs as a quantifier where higher values indicate better results. Among the three MaOO algorithms, the SPEA2+SDE provides the best performance when using Hypervolume indicator to measure Pareto-front quality.

Fig. 3.10 shows the running time of the three algorithms with different user group size. SPEA2+SDE displays certain fluctuations for different group sizes. It is observed that 1) the first ten users have a large volume of data; 2) the shift-based density step takes longer time to process the data; 3) the running time of the three algorithms reaches stable as the user number increases beyond a certain point; and 4) SPEA2+SDE performs better than SPEA2 and NSGA-II in the running time under different user group sizes.

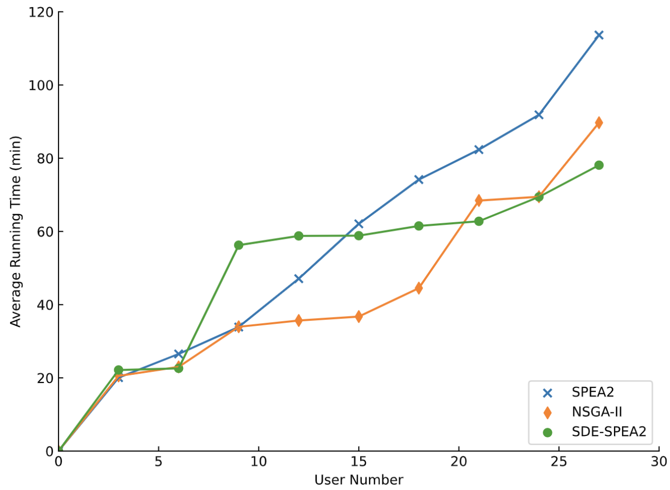

Fig. 3.10 The performance of different algorithms with different user group size.

3.5 Summary

In this chapter, a novel MaOO-based recommendation approach has been developed to provide a balanced and systematic way of dealing with food recommendation tasks. Four crucial objectives (including the user preference, user diet pattern, food nutritional values and food diversity) have been simultaneously considered in the proposed recommendation method. Then, three Pareto-based algorithms have been applied to solve the presented recommendation task, and comprehensive experiments based on real-world data sets have been conducted to verify the effectiveness of the proposed MaOO-based recommendation framework. Some future research directions include 1) the consideration of more user related objectives in the MaOO model; 2) the conduction of more experiments under different food recommendation data sets; and 3) the introduction of machine learning techniques to analyze the food related time series data. Further research topics would include the extension of the main results of this chapter to more comprehensive systems using more up-to-date filtering algorithms [67, 47, 94, 95, 107, 184, 29, 185, 66, 65, 74, 18, 48, 46, 152, 134, 99, 186, 73].

Chapter 4

Sequence-Based Personalized Food Recommendation Systems

4.1 Motivation

The recommender system (RS) is a well-known practical application of the state-of-the-art information filtering and machine learning technologies. Traditional recommendation approaches, including collaborative and content-based filtering techniques, have been widely employed to provide suggestions in RSs, where the user-item interaction matrix is the primary data source. In many application domains, interactions between users and items are more likely to be dynamic rather than static, and thus dynamic user behaviors should be taken into account when solving recommendation tasks in order to provide more accurate suggestions. In this work, we consider the sequentially ordered information from user-item interactions in the RSs where a sequence-based recommendation model is put forward with applications to the food recommendation scenario. Furthermore, the long short-term memory (LSTM) network is employed as the building block to establish such a recommendation model, and a collaborative filtering unit is adopted to make personalized food recommendation. The proposed

LSTM-based RS is successfully applied to a real-world food recommendation data set. Experimental results demonstrate that the developed method outperforms some currently popular RSs in terms of precision, recall, mean average precision and mean reciprocal rank in food recommendation.

Food has always been at the heart of human life. In the past, people had to identify and store food to survive, while in nowadays, people have more concerns about dietary needs including essential nutrition, health, taste, calories, and social occasions [35, 57]. Due to the growing information overload of various food-related content on multimedia, food recommender systems (RSs) are becoming increasingly attractive for people worldwide. Clearly, long-term unhealthy eating habits would be harmful to people's health with potential risks such as the development of undesired chronic diseases. Taking into consideration of the importance of healthy eating habits, the RS is now used as an efficient tool by people to make informed decisions on food selection according to their health conditions, thereby helping people develop heathy eating habits and reduce unaware health risks [113, 178, 177, 179].

Generally speaking, RSs have the advantage of saving time and money by using a series of algorithms to analyze users' food behaviors and ratings so as to recommend the most relevant and appealing foods to users [111]. Note that there are still several challenges (e.g., diversity, adaptation and fluctuation) that hinder the further development and application of RSs. The diversity challenge lies in the fact that food RSs are required to be able to handle diverse types of food preferences of all individuals, e.g., different taste preferences, perceptual abilities, cognitive restrictions, cultural backgrounds, and even genetic influences [147, 120, 183]. The adaptation challenge means that, accounting for the fast change of food trends among people, food RSs are expected to constantly adapt to the latest food fashions in order to provide up-to-date food suggestions [36]. The fluctuation challenge implies that it is unreasonable to supply the users with a one-size-fits-all food recommendation taking into consideration of the dramatic fluctuation of users' food preferences [158]. Faced by the three challenges, there is a practical need to develop a novel recommendation technique to help people select food plans that are reasonable and personalized based on individually diverse, rapidly changing and dramatically fluctuated food preferences.

The collaborative filtering (CF) as well as the content-based filtering (CBF) are two widely used recommendation techniques for food preference learning. Typically, CF works by taking into account the food preferences of users with similar tastes, while CBF focuses on the attributes (e.g., ingredients, nutrition, and reviews) of the food itself [40]. Although CF and CBF achieve reasonable performance for preference learning, their adaptation to the change of user preferences or food contents is poor. To overcome this problem, it is crucial to consider the dynamic pattern of user-item interactions into the recommendation process so as to help better predict future preferences (of users) and optimize recommendation results accordingly. In addition, the consideration of such a dynamic pattern can also provide valuable insights into the interaction between users and recommendation applications/systems, and therefore help improve the user experience [133].

Recently, artificial neural networks have been successfully applied to RSs owing to their strong feature extraction abilities [31, 153, 169, 124, 173, 128, 101]. For example, a convolutional sequence embedding (Caser) RS has been proposed in [153] for product recommendation, where a convolutional neural network (CNN) is employed to capture the sequential features by analyzing the embedding matrix. It is worth mentioning that the embedding matrix can be treated as the "image" of the items in the latent space. Experimental results demonstrate the effectiveness of the proposed Caser RS in extracting sequential patterns by taking both sequential patterns and general preferences into account. In [173], a convolutional attention network has been put forward to explore the user behaviors by unifying a general RS and a sequential RS. A user-based recurrent neural network (RNN) has been developed in [31] for sequence prediction by integrating user information so as to provide personalized recommendation. In [101], a multi-period product RS has been introduced for online food recommendation, where an RNN-based recommendation model is developed to provide product recommendation in multiple time periods.

Serving as a popular RNN, the long short-term memory (LSTM) network has been widely adopted in RSs with hope to comprehensively investigate the dynamic features through user-item interactions [101, 19, 61]. It should be noted that the LSTM network has shown competitive performance in capturing both the long-term and short-term patterns, which contributes to a comprehensive investigation of user behavior in RSs. Motivated by above discussions, it becomes a seemingly natural idea to employ LSTM networks to study the user-item interaction sequences in order to carry out personalized food recommendation. In this chapter, a sequence-based recommendation approach is proposed to lay an effective and systematic basis for establishing food RSs. A traditional LSTM network is adopted to reflect users' food preferences and generate accurate recommendation suggestions. Furthermore, the proposed LSTM-based RS is tested on a public data set, and the experiments verify the promising performance of our approach for food recommendation.

The main contributions of this chapter are outlined in threefold as follows: 1) a unified framework is proposed for food recommendation that leverages feedbacks from sequences as well as historical interactions to model users' long- and short-term preferences; 2) a traditional LSTM network is employed to extract the user representation by considering the user habits at a certain time period; and 3) a series of numerical experiments are conducted on a real-world data set to validate the effectiveness of the developed RS. In summary, the established RS is capable of effectively modeling users' long- and short-term preferences and providing more accurate and diverse food recommendation in comparison with existing food recommendation techniques.

The remainder of this chapter is organized as follows. In Section 4.2, the related work is presented on existing solutions for food recommendation. A sequence-based model is developed in Section 4.3 for food recommendation. The experimental results are discussed in Section 4.4 and appropriate evaluation metrics are carefully selected for evaluating the algorithm performance. Section 4.5 concludes the chapter while pointing out the future directions.

4.2 Related work

In the food domain, RSs play an important role in promoting healthy eating behaviors by approaches such as suggesting healthier food substitutes to users. Food RSs can be divided into three types based on the information used for food recommendation [156]. The first type adopts users' food preference for recommendation, e.g., the search terms or ingredient inputs of users have been utilized in [22] to conduct recipe recommendation. The second type leverages the healthy and nutritional needs of users for recommendation, e.g., a food plan has been generated in [114] based on healthy ingredients instead of harmful ones. The third type finds a trade-off between user preferences and nutritional needs, e.g., a healthy and nutritional meal plan has been made for the elderly in [141] by taking advantage of information from both user preferences and food nutrition.

In comparison with the general RSs, the food RSs have the following differences. The first difference is that the food RSs have to consider more factors when conducting recommendation, e.g., users' nutritional needs, weight goals, and health problems which are primary factors for food recommendation. The second difference is that different domain knowledge and food databases (e.g., nutritional, medical, and dietary information) are required by the RSs to supply users with healthier food suggestions. The last difference is that the unique characteristics (e.g., cooking methods, preparation time, and ingredient combination effects) of various food have to be concerned when making recommendation. In summary, more factors and information should be taken into good consideration by the RSs in order to provide users effective and healthy food plans [44].

For the purpose of improving the accuracy of food RSs, it is crucial to consider both users' dynamic preferences and historical neighbor feedbacks. In this chapter, sequence-based recommender systems (SRSs) are introduced to capture dynamic preferences of users. Modeling the sequential pattern of users' behaviors allows the RSs to understand the evolution of user tastes over time, thereby providing better recommendation [174]. It is worth mentioning that the SRSs are different from traditional RSs in that SRSs account for the order of items via the perspective of users' historical behaviors, and thus both timing and frequency of interactions are taken into account for recommendation [38]. So far, the SRSs have been successfully applied in many applications such as e-commerce, music, and news recommendation [62, 70, 121, 17, 71, 45].

Incorporating sequence-based RSs into food recommendation has several advantages. First, food recommendation is often time-sensitive where suggestions are expected to be interactive. For example, if a customer has ordered a steak, it is reasonable for RSs to recommend a salad as a starter and a glass of red wine as an accompaniment. Second, SRSs make it possible to model the rather complicated couplings/interactions among different foods that are consumed together. For example, SRSs can capture the fact that consuming bread increases the likelihood of subsequently consuming milk. Third, SRSs are effective at handling implicit feedbacks that are more reliable than the explicit feedbacks (ratings) which are not always available [163].

Existing solutions for SRSs mainly fall into two categories which are the Markov chain models and deep learning techniques. The Markov chain model treats the users' behavior as a sequence of states and item recommendation is provided based on the state transition probabilities [139, 11, 58]. As for the deep learning techniques, typical examples are CNNs, RNNs, and graph neural networks, which have been widely used in a variety of sequence-based RSs [61, 31, 153, 30, 173]. Although the SRS has been implemented in a variety of domains, it has been rarely considered in the food domain due to the fact that food recommendation is a highly contextualized and personalized task which unavoidably leads to significant difficulties to the satisfactory design of SRSs. As such, we are motivated to investigate a specialized food recommendation approach that effectively integrates the SRSs with other types of RSs to provide a comprehensive and personalized solution for food recommendation.

4.3 Sequence-based deep learning model for food recommendation

In this section, the recommendation task is described with elaborated descriptions of the proposed model. We start by introducing some key concepts required for the model.

4.3.1 Problem formulation

Consider a set of m users $\mathscr{U} = \{u_1, u_2, \ldots, u_m\}$ and a set of n items $\mathscr{I} = \{i_1, i_2, \ldots, i_n\}$, where m and n are the sizes of the user set and item set, respectively. For user u_i, it has an ordered list of items $\mathscr{S}^{u_i}$ according to the action sequences. For each user u_i, the prediction task can be written as:

$$\mathscr{S}^{u_i}_{t-L}, \cdots, \mathscr{S}^{u_i}_{t-2}, \mathscr{S}^{u_i}_{t-1} \rightarrow \mathscr{S}^{u_i}_{t} \tag{4.1}$$

where t for $\mathscr{S}^{u_i}$ denotes the temporal order in which actions happen. Given sequence $\mathscr{S}^{u_i}_{t-L}, \cdots, \mathscr{S}^{u_i}_{t-2}, \mathscr{S}^{u_i}_{t-1}$, the model tries to predict $S^{u_i}_t$ as the next item with which the user will interact. Two sequential patterns are considered in this chapter, i.e., the point-level sequential pattern (PSP) and the union-level sequential pattern (USP).

Point-level sequential pattern

The point-level sequential pattern (PSP) is a type of sequence-to-point learning model, where predictions are made based on all the actions that have occurred up to a certain time point [181]. As shown in Fig. 5.1 (a), the output $\mathscr{S}^{u_i}_t$ is a predicted item for the next action. All of the previous points influence the target independently. For example, if we have a list of items ingested by a person over the course of a day, we may be interested in finding two possible patterns, e.g., "coffee is usually consumed after dessert" and "chips are usually consumed after fish."

Union-level sequential pattern

The USP tries to predict the behavior of users based on aggregating multiple interactions [87]. The pattern is based on the assumption that the union of all the event is a reasonable predictor for the next event in the sequence. Different from the PSP, the USP is able to identify items that are frequently co-consumed, such as the combination of breakfast and lunch. Fig. 5.1 (b) shows an illustration of the PSP, where several previous actions jointly influence the target action. The LSTM network is employed in our proposed approach to mine both PSP and USP that exist in users' behaviors.

4.3.2 Modeling and learning

The proposed model mainly consists of two units, i.e., the LSTM unit and the CF unit, where the LSTM network attempts to discover long- and short-term preferences that

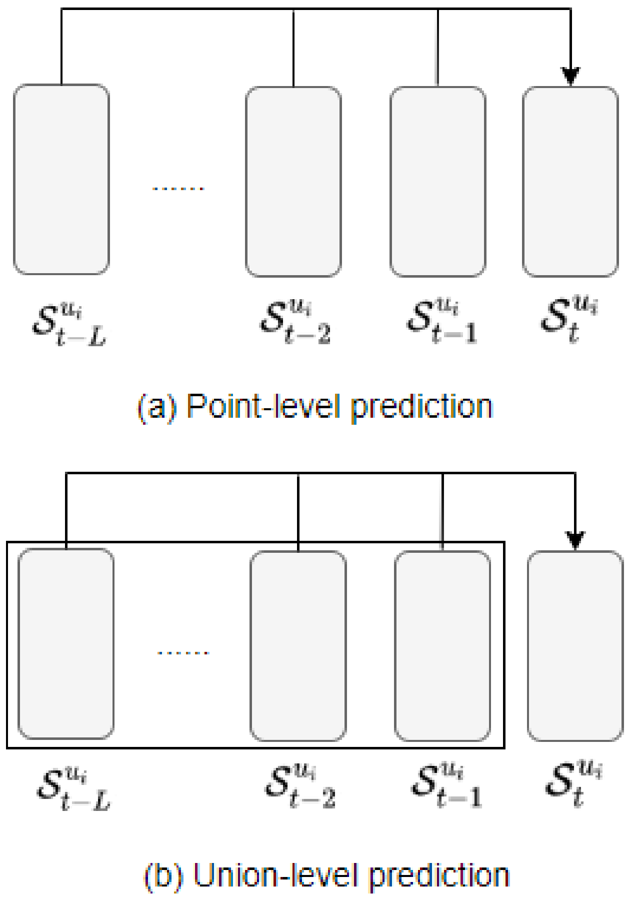

Fig. 4.1 Point and union-level sequential patterns.

exist in users' interaction sequences and to determine the latent representation of the user in the embedding layer. The sequential learning process allows the model to learn behavior patterns of users' preferences at both point- and union-level, which enables the model to make more accurate predictions about their future behaviors.

Specifically, the user-item interaction at each time step is transformed into one-hot encoded vector as the network input. Then, these vectors are mapped to low-dimensional dense vectors through the embedding layer and passed to the LSTM network to capture the behavior pattern of each user. Afterward, the user embedding vector is calculated by averaging the trained embedding vectors. The results are fed as input vectors for the CF unit.

The CF unit makes recommendation by suggesting items (liked by other users with similar tastes) to target users. Cosine similarity is used to quantify the correlation between two users. After obtaining the similarity matrix, the most similar group of users (to the target users) is identified with the most liked item selected and forwarded to the target users as recommendation.

LSTM networks

Recurrent neural networks (RNNs) use data patterns to predict the probability of future events based on the sequential characteristics of the data [108]. Various ordinal or temporal problems can be solved using this method, such as language translation, natural language processing, speech recognition, and image captioning. In contrast to traditional deep neural networks, which assume that inputs and outputs are independent of each other, RNNs incorporate input and output information from previous inputs to influence the current input and output. The LSTM network, as a variation of the traditional RNN, is designed to better retain information over a long period of time.

In addition to learning the non-linear and non-stationary nature of sequential data, the LSTM network has the advantage of preserving information in memory for a long period of time, which is in line with the goal of capturing the union-level pattern. The LSTM network controls the flow of information using three gates: the forget gate, the input gate, and the output gate, where the forget gate determines which information requires attention and which may be ignored by using the update function given as follows:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{4.2}$$

where a sigmoid layer is applied on the input of the unit at time t and the last cell state, denoted by x_t and h_{t-1}, respectively. The next step is to determine what information should be stored in the current cell state. First, the input gate layer determines which values to update. Then, a tanh layer formulates a vector consisting of the values of new candidates, denoted as $\tilde{C}_t$, which can be added to the state. Such two layers combine to produce an update to the current state, which is defined as follows:

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{4.3}$$

$$\tilde{C}_t = \tanh\left(W_C \cdot [h_{t-1}, x_t] + b_C\right) \tag{4.4}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{4.5}$$

The new cell state C_t is decided by the old state $f_t * C_{t-1}$ and the new candidate value $i_t * \tilde{C}_t$. Finally, the output is generated from the current internal cell state C_t.

$$o_t = \sigma\left(W_o [h_{t-1}, x_t] + b_o\right) \tag{4.6}$$

$$h_t = o_t * \tanh\left(C_t\right) \tag{4.7}$$

where the values of the current state x_t and the previous hidden state h_{t-1} are passed into the sigmoid function to decide which parts of the cell state are to be updated. Then, the new cell state passes through the tanh function. Both of these outputs are multiplied point by point. The final hidden state h_t is used for prediction.

Customized the LSTM network

The LSTM network is used in this chapter to learn user representation. The input of the LSTM network is the item of the actual interaction, while the output is the predicted item which a user tends to interact with at next time step. The item is first converted to a one-hot encoding vector, where the length of the vector equals the number of items. Here, only the coordinate corresponding to the active item is one, and the rest coordinate are zeros. Then, the one-hot encoding is mapped to a learnable, low-dimensional vector through the embedding layer. After retrieving the pre-trained item embeddings, the user embedding can be calculated by averaging item embeddings. Note that the pre-trained process is independent for each user, and therefore the averaging embedding can be used as the reasonable representation for each user. Fig. 5.2 depicts the structure of the LSTM unit. Additional embedding layers are added between the input and the LSTM layer, and the output is the predicted preference of the items.

CF unit

The CF unit starts with user embedding that represents the individual interest of each user. The user embedding, which is a fixed-length vector representation of a user's interests or preferences, is generated by an LSTM network unit. To find the user group most similar to the target user, the similarity between each pair of user embeddings is calculated using the cosine similarity measurement. The cosine similarity is a measure

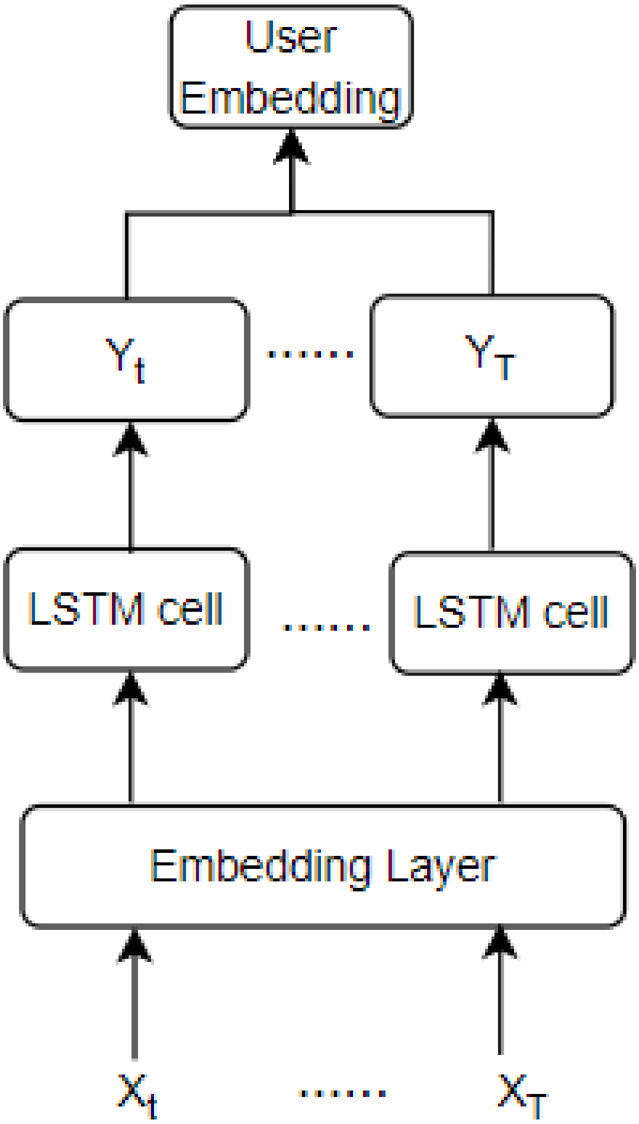

Fig. 4.2 General structure of the network.

of similarity between two vectors in a high-dimensional space, and it ranges from -1 to 1. A value of 1 means that the two vectors are identical, while a value of -1 means that they are completely dissimilar. The cosine similarity is defined as:

$$\text{sim}(x,y) = \frac{x \cdot y}{\|x\| \|y\|} \tag{4.8}$$

where $\|\cdot\|$ is the Euclidean norm of vector "$\cdot$". Conceptually, $\|\cdot\|$ is the length of the vector. The measure computes the cosine of the angle between vectors x and y. The greater the cosine value is, the more similar the tastes of the two users are. The next step is to generate the recommendation. The top N most liked items have been retrieved from the target users' neighborhood based on their popularity, and the recommendation lists are ranked according to their relevance and popularity. Table 5.1 provides the similarity matrix acquired from the CF unit.

After computing the cosine similarity between each pair of user embeddings, the results are stored in a similarity matrix, which is a square matrix where the element at position (i,j) represents the cosine similarity between the ith and jth user embeddings. It should be noted that the similarity matrix is symmetric, which means that the element at position (i,j) is the same as the element at position (j,i). This is because the cosine similarity between two vectors is symmetric. The diagonal elements of the similarity matrix (i.e., the elements where i=j) represent the similarity between a user and itself. Since the cosine similarity between a vector and itself is always 1, the diagonal elements of the similarity matrix will all be equal to 1. The off-diagonal elements of the similarity matrix represent the similarity between two different users. The values of these elements range from -1 to 1, where a value of 1 indicates that the two users are identical, and a value of -1 indicates that they are completely dissimilar.

Table 4.1 Similarity Matrix.

user_id	1	2	3	4	5	6	7	8
1	1	-0.79	0.60	-0.76	0.84	-0.78	0.79	0.57
2	-0.79	1	-0.57	0.88	-0.93	0.93	-0.91	-0.60
3	0.60	-0.57	1	-0.54	0.63	-0.56	0.64	0.68
4	-0.76	0.88	-0.54	1	-0.90	0.93	-0.92	-0.54
5	0.84	-0.93	0.63	-0.90	1	-0.96	0.95	0.66
6	-0.78	0.93	-0.56	0.93	-0.96	1	-0.95	-0.61

4.4 Implementation and experiments

In this section, the proposed model is evaluated against popular baselines on one of the most popular food data sets, i.e., the Food.com data set which is previously the GeniusKitchen.com data set.

4.4.1 Data set

The website Food.com is arguably the largest food-oriented website that attracts 1.5 billion visits every year, and the adopted data set is comprised of 180K+ recipes as well as 700K+ reviews that cover user interactions for 18 years. Each interaction in the data set consists of a user identifier, a recipe identifier, and the corresponding rating and date. For better model performance, the explicit feedbacks has been converted to the implicit feedback.The website allows users to create and share recipes, rate and review recipes, and interact with other users in a social media-style environment. To collect the data used in this study, the researchers scraped the food.com website using web scraping techniques.

Table 5.4 shows some examples of the Food.com data set. The user_id and recipe_id represent the user identifier and the recipe identifier, respectively. The date indicates the record time of this entry and the interactions identify that the user has consumed the item.

Table 4.2 Food.com data set.

user_id	recipe_id	date	interaction
1	122140	2011.01.04	1
1	77036	2011.01.05	1
1	156817	2011.01.06	1
1	76957	2011.01.07	1
1	68818	2011.01.08	1

4.4.2 Evaluation Metrics

The goal of the experiments is to evaluate the quality and performance of the proposed approach against various baselines. For each user, the last 20% interactions are held as the test set and the remaining data are utilized for training. The performance of the utilized RSs is measured by precision@N, recall@N, mean average precision (MAP), as well as mean reciprocal rank (MRR). Precision refers to the number of retrieved items that are relevant, while recall indicates the number of relevant items that are retrieved. Precision@N and Recall@N are defined as:

$$\text{Prec}\ @N = \frac{\left|R \bigcap \hat{R}_{1:N}\right|}{N} \tag{4.9}$$

$$\text{Recall}\ @N = \frac{\left|R \bigcap \hat{R}_{1:N}\right|}{|R|} \tag{4.10}$$

where $\hat{R}_{1:N}$ denotes a list of top-N predicted items for a user and R denotes the last 20% of actions in the test set. To evaluate the overall performance of the approach, the MAP and MRR are used. The MAP is widely used in the RS for its ability to provide general estimation of model performance. The MAP is the average of the average precision (AP) defined by:

$$\text{AP} = \frac{\sum_{N=1}^{|\hat{R}|} \text{Prec}\ @N \times \text{rel}(N)}{|\hat{R}|} \tag{4.11}$$

where $\mathrm{rel}(N) = 1$ if the $N-th$ items are in the same ranking order in both prediction and test sets. The MRR is used to assess the performance of a CF unit and calculated as the mean of the reciprocal ranks of the items retrieved by the approach. The MRR is defined as:

$$\mathrm{MRR} = \frac{1}{|Q|}\sum_{i=1}^{|Q|}\frac{1}{\mathrm{rank}_i}. \tag{4.12}$$

4.4.3 Experiment Setting

In this chapter, three widely used baselines (including the Item k nearest neighbor (Item-KNN) algorithm [91], the Meta-Prod2vec collaborative filtering (MPCF) algorithm [162], and the convolutional sequence embedding recommendation (Caser) algorithm [153]) are selected as the benchmark.

- Item-KNN: Item-KNN recommends items similar to the target item, and similarity is defined as the cosine similarity between the vectors of the user interaction history.
- MPCF: The Meta-Prod2vec method computes low-dimensional embeddings of items based on previous interactions with the items. The representation of a user is calculated as the mean of the products consumed by the user.
- Caser: A personalized top-N sequential recommendation framework which uses CNNs for sequence modelling.

The recommended item numbers are set to be 1, 5, and 10 in the experiment to evaluate the performance of the utilized RSs. The learning rate, the minimum epoch and the mini-batch size of the MPCF algorithm, the Caser algorithm and the proposed approach are set to be 0.001, 50 and 128, respectively. The numbers of horizontal filters and the vertical filters of the Caser algorithm are set to be 16 and 4, respectively. In the proposed approach, the number of layer and the size of hidden neurons are set to be 1 and 30, respectively.

4.4.4 Performance Comparison

The evaluation results of the three baselines and the proposed approach are presented in Table 5.3, where the best performer in each row is highlighted in bold, and the last column also included the improvement of the proposed approach over the best baseline in percentages. As shown in Table 5.3, the proposed method outperforms the Item-KNN method, the MPCF method, and the Caser method in terms of Prec@5, Prec@10, Recall@5, MAP and MRR. In addition, the proposed method obtains the second-best results in terms of Prec@1, Recall@1 and Recall@10 comparing to the other three baseline methods. In general, we can draw the conclusion that the proposed method outperforms the baseline methods with respect to the four chosen evaluation metrics. It should also be noted that sequential RSs (e.g., MPCF and Caser) outperform the Item-KNN method (which is the traditional RS), suggesting that the considered sequential patterns in user behaviors lead to higher accuracy.

Table 4.3 Performance comparison

max width=

Metric	Item-KNN	MPCF	Caser	Proposed Model	Improvement
Prec@1	0.0214	0.0257	**0.0284**	0.0281	-1.05%
Prec@5	0.0188	0.023	0.0244	**0.0249**	+2.04%
Prec@10	0.0199	0.0203	0.0209	**0.0226**	+8.13%
Recall@1	0.0428	0.0514	**0.0569**	0.0562	-1.23%
Recall@5	0.0564	0.0692	0.0732	**0.0748**	+2.18%
Recall@10	0.0796	0.0814	**0.0838**	0.0815	-2.74%
MAP	0.06385	0.08398	0.08465	**0.08606**	+1.66%
MRR	0.06102	0.06962	0.07403	**0.08003**	+7.49%

In our experiment, the embedding dimension is a key hyper-parameter which is optimized through the model selection process. To obtain an optimal solution of the embedding dimension, we adopt the embedding dimension from 10 to 100, and compare the MAP of two baselines with that of proposed model on different embedding dimensions, as shown in Fig. 5.3.

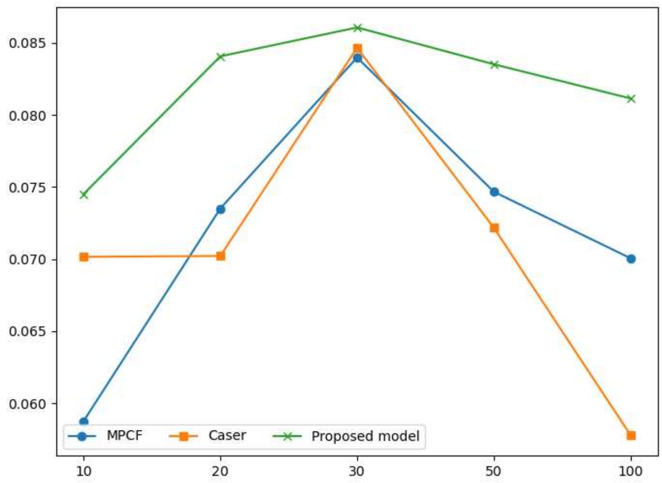

Fig. 4.3 MAP (y-axis) vs. the number of the latent dimension d (x-axis).

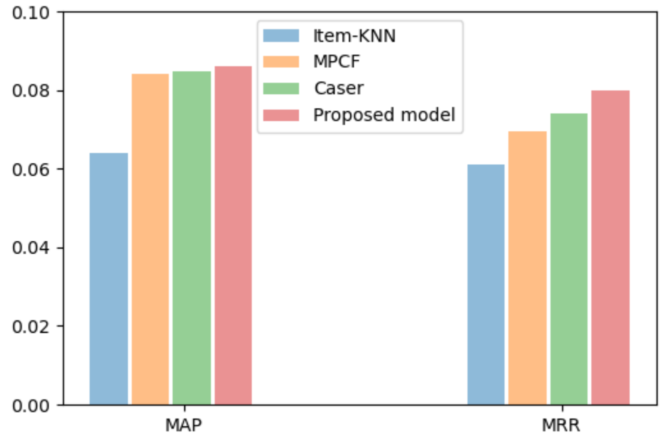

Fig. 4.4 Comparing Prec@10 and Recall@10 of the proposed solution against three baselines.

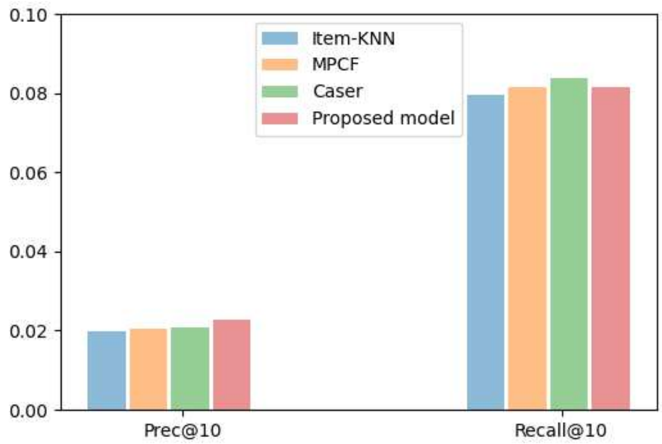

Fig. 4.5 Comparing MAP and MRR of the proposed solution against three baselines.

Fig. 5.3 shows the MAP of two baseline plus the proposed model based on different embedding dimensions. Among these baselines, the MPCF, Caser, and the proposed method achieve their best performance with the embedding dimension of 30. It should be noted that performance does not improve with the increase of the dimension. Overall, the proposed model beats the strongest baseline based on the selected range and shows a rather steady trend compared to other baselines, which verifies the stability of the approach. Fig. 4.4 and Fig. 4.5 compare the proposed solution against Item-KNN, MPCF and Caser on four metrics in the form of bar charts.

4.5 Summary

In this chapter, a novel sequence-based recommendation approach has been developed to solve food recommendation tasks. Specifically, LSTM networks are used to approximate user-item interactions where CF techniques are adopted to make recommendation. Experimental results show reasonable performance gains over the popular baseline of the sequence-based RSs. Some future research directions include 1) the adoption of additional information (e.g., images, reviews and browsing history); 2) the proposal of explainable and personalized food recommendation; and 3) the introduction of more advanced machine learning techniques for cross-domain recommendations, see e.g. [92, 182, 168, 103, 105, 23, 175, 176, 104, 137, 54, 103, 60].

Chapter 5

A Deep Graph Neural Network-Based Strategy for Food Recommendation

5.1 Motivation

Graph neural networks (GNNs) have recently been ranked as one of the most advanced neural networks and has found wide applications in various fields including chip design, problem reasoning, and traffic flow prediction. In recommendation systems, GNNs have also been deemed as a promising tool for capturing the complex user-item interactions. When applying the GNNs to recommendation systems, a common approach is to generate a bipartite graph to describe the user-item interactions due to its capabilities of accurately making predictions about unknown connections and efficiently learning the underlying patterns and relationships between the nodes in the graph. In this paper, by means of the temporal dependent GNNs and the data augmentation technique, a new strategy is proposed to convert the recommendation task into a predicting problem of unknown node connections in the graph. Experimental results on real-world data sets demonstrate the superiority of the proposed strategy over the commonly used methods.

Due to the ever-increasing development of various internet technologies, people are frequently surrounded by abundant information and encountered with the difficulty of obtaining interested information. Disseminators of information are always struggling to communicate their message to intended audience effectively, and an efficient approach to achieving this goal is to apply the recommendation systems (RSs) that connect users and information together [24]. Typically, the RSs are capable of helping users find valuable information from the massive amount of available data and allowing information to be presented to interested users.

The information overload is widely confronted in a variety of areas including the food domain [57] where users are presented with an increasing amount of dietary information as the living standard increases. As a matter of fact, it is a great challenge to identify the intended food items (beneficial to user health) from the abundant food choices [35]. To address this challenge, the RSs are widely employed to assist customers in handling abundant information. Unlike traditional RSs (e.g. the movies and music RSs), food RSs provide users with a convenient way to guide them towards favourable foods that are good to their health [44]. As such, the food RSs have gradually become a vital tool in promoting healthy living habits among individuals.

In the practical application of food RSs, a common approach is to convert the recommendation problem into a matrix completion task which is later solved by different recommendation algorithms to predict users' preferences, such as the content-based or collaborative filtering algorithm [158]. Unfortunately, the content-based or collaborative filtering algorithm often fails to provide adequate recommendation results due to limited available data and various complex factors (e.g. genetics, geography, and economic considerations) contributing to the users' preferences. This makes it difficult for the RSs to accurately model the users' preferences, thus resulting in low recommendation accuracy. Instead of converting into a matrix completion task, the food recommendation task can also be regarded as a graph-structured data analysis problem

[127], which provides an effective way to 1) analyze user behaviors from streaming data sources and 2) discover the user-item relationships as well as the relationships between the connected data points, patterns and trends.

In graph neural network-based food RSs, network connections are constantly changing over time, and it is essential to predict users' dynamic behaviours according to different applications, such as recommending new friends in social networks and suggesting items to customers in e-commerce networks [11]. In essence, the food recommendation task can be regarded as a prediction problem of missing links in a connected user-item graph by taking into account the fact that the user-item interactions are easy to be interrupted if the user starts to consume a specific type of food or recipe.

To represent food items as nodes in a graph and capture their relationships using edges, different graph construction strategies are utilized. These strategies focus on various aspects of food items, including their nutritional content, ingredient similarity, user behavior, or social networks [33]. To train the model and make accurate recommendations, Graph Neural Network (GNN) architectures are employed, such as Graph Convolutional Networks (GCNs), Graph Attention Networks (GATs), and Graph Recurrent Neural Networks (GRNNs). Several GNN-based recommendation models have been developed, including GC-MC [6], PinSage [138], NGCF [132], LightGCN [59], and KGAT [131], which differ in their approaches to graph construction, node representation learning, and information propagation. Despite their differences, these models have a shared objective of enhancing the accuracy and scalability of recommendation systems by utilizing graph structures and exploiting the relationships among users, items, and their attributes.

So far, various strategies have been developed for graph neural network-based food RSs to tackle the previously outlined issues in order to acquire accurate network representation and food recommendation. A main challenge here is the generation of proper node representation from graph-structured data, and a good solution to this challenge is the so-called representation learning method [50]. Nevertheless, such a method usually generates low-dimensional latent representation in case of complex high-dimensional data and moreover, can only be applied to fixed networks where users' temporal information is not considered.

The main contribution of this chapter can be summarized as follows: 1) better recommendation results are obtained by transforming the recommendation task into a graph-based link prediction problem; 2) data diversity and model robustness are improved by introducing the augmentation technique in data processing; and 3) prediction accuracy is enhanced by considering users' temporal behaviors into the network.

The rest of the chapter is organized as follows: Section 5.2 presents the related work on graph neural network for recommendation system. Section 5.3.1 develops a graph neural network-based strategy for food recommendation. Section 5.4 discusses the experimental results and the corresponding metrics chosen for algorithm evaluation. Section 5.5 presents some conclusions.

5.2 Related work

Most of the data in the recommendation system can be regarded as graph-structured data, for example, the users' interaction behavior on items (click, browse, purchase, etc.). By converting user-item interactions into nodes and edges on bipartite graphs, recommendation tasks can be regarded as prediction problems of missing links in the graph. With the development of the graph learning (GL) approach, the application of GL-based methods, particularly the graph neural networks (GNNs), have been extensively studied for recommendation systems [127].

In comparison to traditional collaborative filtering approaches, Wang et al. [132] suggested a spatial GNN for recommendation that achieves greater performance [86] [63]. To solve problems of cold start, scalability, individualization and dynamics of recommendation systems, Gao et al. [52] reviewed and summarized the GNN approach on the recommendation task based on the knowledge graph (KG). For real-world platforms, Ying et al. applied the GNN-based model to web-scale recommender systems successfully and quickly [138].

As a sub-domain of the recommendation system, the food recommendation system focuses on providing users with personalized suggestions for food-related products and services. Two main approaches have been widely applied in the food recommendation domain, e.g. the content-based and collaborative filtering approaches [111]. The content-based approach relies on the information associated with the items (such as item attributes, ingredients and reviews) to recommend items similar to users' past preferences. The collaborative filtering approach, on the other hand, uses the ratings of other users to determine the similarity between presented and recommended items. However, such approaches are limited in their ability to capture more complex representations of user-item interactions and contextual information.

Incorporating GNNs into food RSs can enable more accurate prediction of user preferences and better personalized recommendation as GNNs can effectively capture the semantic information and structure of the graph [50]. To be more specific, GNN-based models can capture both structural connection and high-order similarity between users and objects, and the semantics is expanded that users with comparable interactions would have similar preferences through repeated instances of information propagation.

5.3 Dynamic GNNs for food recommendation

The proposed model consists mainly of two units: (1) the data augmentation unit and (2) the link prediction unit. The former unit has enhanced all user data, while the latter predicts whether two nodes will generate a link at a specific time. The network input is generated by converting user-item interactions at each time step into one-hot encoded vectors. The embedding layer then transforms the vectors into lower-dimensional dense vectors which are subsequently fed into the link prediction unit to identify the behaviour pattern of each user.

5.3.1 Data augmentation

Machine learning models often require extensive data sets to precisely estimate various parameters to achieve the optimal performance. Due to limited amount of available data and the high cost of collecting additional data, the data augmentation technique is thus adopted to create artificial data based on the original data set [51].

The data augmentation technique involves a range of strategies such as random cropping, scaling, image inversion and generative adversarial networks [123]. With the help of this technique, the size and quality of the training data is increased, and the classification accuracy is improved [129]. By transforming a small amount of data into a larger set, the range and quantity of training examples are significantly increased, enabling models to capture more complex patterns in the data. It is worth pointing out that the potential of the augmentation technique has not yet been fully explored in food RSs, although it has been widely adopted as a feasible solution for training more robust models in various fields.

Our strategy starts by applying data augmentation to generate a synthetic time series to enhance users' daily food consumption records, and then the dynamic time warping (DTW) and the DTW barycentric averaging (DBA) are used to augment the users' daily food consumption records [41].

Definition 1: Time Series A time series $T = \langle t_1, \ldots, t_L \rangle$ is an ordered set of real values where L denotes for length. A data set $\mathbf{D} = \{T_1, \ldots, T_N\}$ is a collection of multivariate time series.

By taking a set of time series from the users' record, e.g., consecutive days of food consumption, we calculate the weighted average time series $\bar{T}$ and then use this average series as a new synthetic one to augment **D**. In order to be flexible, the identical length of time series may vary for different users due to their limited size of records, and the DTW is thus used to compare two temporal sequences of varying lengths. It should be noted that an important contribution of our strategy is to adjust the weights so that the recently consumed items contribute more information. In *Definition 1*, the DTW is used to calculate the distance between two time series and the DBA is used to obtain the average series, where T stands for food consumed by users in a certain period and

Definition 2: Dynamic Time Warping Given two sequences Q and C, $W = w_1, w_2, \ldots, w_\mathrm{k}$ stands for the wrapping path, where the k-th element of W ($W_k = (i, j)_k$) is the mapping elements of the sequence Q and C. By minimizing the equation 5.1, the shortest wrapping path between two sequences is obtained. The DBA uses an expectation-maximization to obtain the weighted sequence by iteratively updating $\bar{T}$, as defined in equation 5.2.

$$DTW(Q,C) = \min \left\{ \sqrt{\sum_{k=1}^{K} w_k / K} \right. \tag{5.1}$$

Definition 3: DTW Barycentric Averaging (DBA)

$$\arg\min \bar{T} \in E \sum_{i=1}^{N} DTW^2 \left(\bar{T}, T_i\right) \tag{5.2}$$

5.3.2 Dynamic GNNs

Link prediction is one of the most common tasks in GNNs. The objective is to identify unknown network connections based on existing network data. The link prediction problem is regarded as a supervised learning task, where the past network structure data is utilized to estimate how users will behave in future periods [125].

Definition 4: Dynamic Graph A dynamic network defined as $G = \left(V, E^T, T\right)$, where V is the vertex set, E^T is the edge set and T is the time set. In the dynamic graph, $e^t_{i,j}$ is the edge which indicate two vertices i, j generate an edge at time t.

Definition 5: Link Prediction. Let the dynamic network G and edge $e^{t_0}_{i,j}$ be given, the goal of link prediction is to predict whether new edges i, j will be generated for a given time $t > t_0$.

The temporal dependent graph neural network (TDGNN) [125] is adopted in our strategy, where a simple framework for learning network representation is formulated that combines temporal information of user-item interactions with GNNs. The TDGNN takes a dynamic graph $G = \left(V, E^T, T, X\right)$ as its input, where $X = \{\overrightarrow{x_1}, \overrightarrow{x_2} \ldots, \overrightarrow{x_n}\}$, $\overrightarrow{x_i} \in R^P$ is the vector representation of the node with n being the number of nodes and P being the dimension of the node feature. For every two nodes in the graph, connections are generated at different time points. The TDGNN estimates the unknown link prediction at future time points by aggregating edge representations.

As shown in Fig. 5.1, the input of the network is the graph data, which consists of a set of nodes and edges with associated features. The graph can be represented as an adjacency matrix, and the features can be represented as feature matrices associated with each node and edge. The next step is to initialize the node embeddings, which represent the initial state of each node in the graph. The message passing layer is the core of the GNN model. In this layer, each node in the graph sends messages to its neighboring nodes and updates its own state based on the messages it receives. This process is repeated for multiple iterations, allowing each node to aggregate information from its neighbors and refine its representation. After the message passing layer, the graph representation is computed by applying a readout function to the final node embeddings. The readout function aggregates the node embeddings to compute a

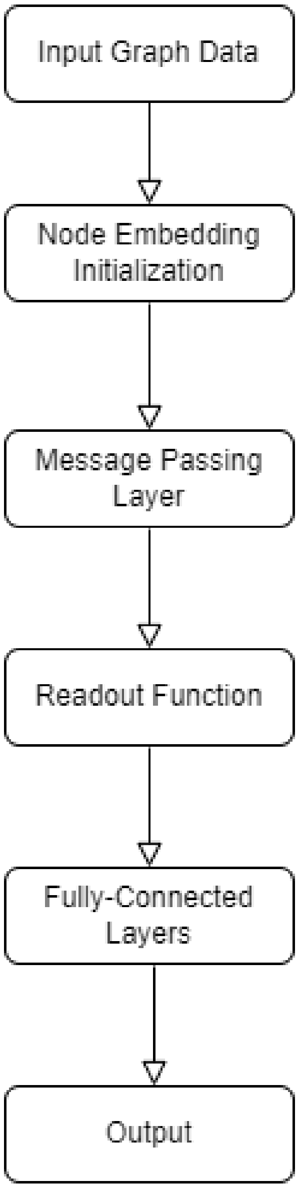

Fig. 5.1 Diagram of TDGNN structure

graph-level representation. Finally, link prediction is performed by feeding the output of the TDGNN model through a fully connected layer with a sigmoid activation function and the output indicate whether or not the link is existed.

In order to acquire edge representations, let us assume that v is the node for which the representation needs to be calculated, and the initial representation of v can be represented as $\overrightarrow{h_v^0} = \overrightarrow{x_v}$. The new node representation at time t can be calculate by aggregation function as follows:

$$\vec{h}_v^k = \sigma \left(\sum_{u \in N_t(v) \cup v} \alpha_{vu}^t W \vec{h}_u^{k-1} \right) \tag{5.3}$$

In equation 5.3, σ represent the nonlinear activation function, and the set of neighbor nodes of the target node v at time t is denoted as $N_t(v)$. The the learnable shared weight matrix is represented as W. The neighbor nodes aggregating weights α_{vu}^t at time t can be calculated as follows:

$$\alpha_{vu}^t = \frac{e^{t-t_{v,u}}}{\sum_{u \in N_t(v) \cup v} e^{t-t_{v,u}}} \tag{5.4}$$

where $t_{v,u} \in T$ represents the edge generating time between node v and u. Four EdgeAggs edge aggregation functions have been adopted in this work for experiment comparison, as shown in Table 5.1.

Table 5.1 Edge Aggregation

EdgeAgg	Definition
Average(Ave)	$\frac{h_v+h_u}{2}$
Hadamard(Had)	$h_v \circ h_u$
Weighted-L1(W-L1)	$\|h_v - h_u\|$
Weighted-L2(W-L2)	$\|h_v - h_u\|^2$

5.4 Experiments

To evaluate the performance of the proposed strategy, we conduct experiments on one of the most popular food datasets as described below.

5.4.1 Data sets and Experimental setting

MyFitnessPal (MFP), a free mobile application, tracks users' daily food consumption and calculates the number of consumed calories. The MFP database contains information on 9800 individuals' meals between September 2014 and April 2015, including details on 710,000 different food items, with a total of 1.9 million entries.

Table 5.2 MyFitnessPal Data Set

user_id	date	meal_sequence	food_ids
1	2014.10.15	1	1,6,47
57	2014.11.15	1	1,17,6,48,41
87	2015.12.15	1	1,9,69,46,7
115	2015.01.15	1	1,67,6,71,9,75
140	2015.02.15	1	1,68,6,7,41,109

Table 5.4 provides five examples of the MFP data set. The user_id and date represent the identity of the user and the time required by this entry, respectively. The meal_sequence number denotes the order of the meals on a given day, for example, if the meal_sequence is 1, it means that it is the first meal of the day. The food_ids records food entries that users have consumed.

As shown in Fig. 5.2, the majority of user-item interactions are contributed by the top 20% of users, a pattern known as the long tail phenomenon.Fig. 5.3 illustrates the augmented dataset in which each user's record has been increased twofold.Experiments is conducted using the dataset both with and without data augmentation.

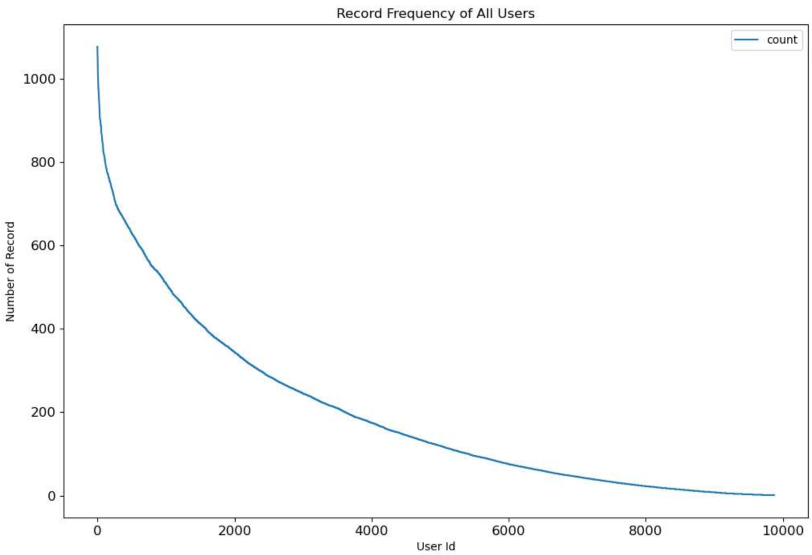

Fig. 5.2 Record Frequency of All Users.

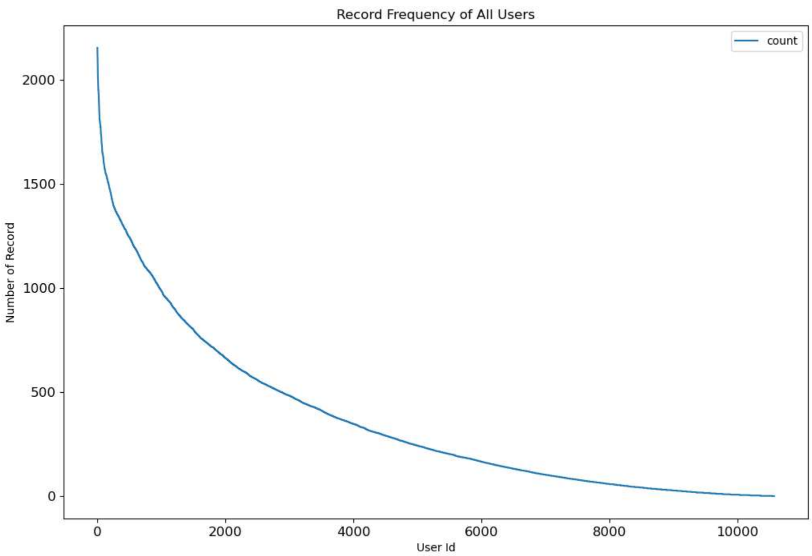

Fig. 5.3 Augmented Record of All Users.

5.4.2 Performance Comparison

First, we evaluate the proposed model using different edge aggregation functions, which is derived from [125]. The comparison results are listed in Table 5.3.

Table 5.3 Performance comparison

	Ave.	Had.	W-L1	W-L2
Org.	0.7803	**0.9106**	**0.9507**	**0.9764**
Aug.	0.9481	**0.9540**	**0.9853**	**0.9922**

In this set of experiments, we aim to evaluate the effectiveness of the proposed model in comparison to various baseline models. One of the baselines is the graph convolutional networks (GCNs) model, which is a widely-used technique for learning node representations in graph data. GCNs leverage a localized, initial estimate of spectral graph convolution to efficiently learn node representations. Another baseline that we will be evaluating is Bayesian Personalized Ranking (BPR) from Implicit Feedback. BPR is a collaborative filtering technique that is commonly used in recommendation systems. It works by modeling the preferences of users based on the items they have interacted with in the past. We will compare the performance of the proposed model against these baselines, both with and without data augmentation.

The Table 5.3 demonstrates that various edge aggregation functions can affect the precision of the classification.Weighted-L2 achieves better performance when compared to other aggregation techniques.Additionally, the augmented data set has demonstrated an overall enhancement to all the aggregation techniques.

In order to evaluate the proposed model more effectively, we compare the proposed model with graph convolutional networks (GCNs) model, which is the most representative GNNs-based learning technique. The GCNs leverage a localized, initial estimate of spectral graph convolution to learn node representation efficiently. We compare the performance of the two methods with and without data augmentation.

For the MFP dataset, we first sort the data set in ascending order based on the timestamp of each record, and then we select the top 80% as the training set and the remaining 20% as the testing set. The Area under ROC curve (AUC) [64] is used to measure the model's classification accuracy, and is calculated by measuring the area beneath the ROC curve and the x-axis.

Table 5.4 Performance comparison

	GCN	BPR	Improv.
Org.	0.7803	0.886	**0.7915**(+1.12%)
Aug.	0.9481	0.896	**0.9351**(+1.3%)

Table 5.4 presents a performance comparison of the proposed model against two baseline models: Graph Convolutional Networks (GCN) and Bayesian Personalized Ranking (BPR). The table reports the performance of each method in terms of the Area Under the Receiver Operating Characteristic Curve (AUC score). The results show that the proposed model outperforms both baselines in both the original and augmented settings, with statistically significant improvements over both models. Specifically, the proposed model achieves an AUC score of 0.7803 in the original setting, compared to 0.886 for BPR and 0.9481 for GCN. In the augmented setting, the proposed model achieves an AUC score of 0.9351, compared to 0.896 for BPR and 0.9481 for GCN. The table suggests that the proposed model is a promising approach for the binary classification task at hand, outperforming established techniques and achieving improvements in AUC score even in the presence of data augmentation.

The evaluation results of the GCN and the proposed approach are presented in Table 5.3, where org. in the table represents the original data set and aug. stands for the augmentation data set. It is seen from the table that our approach exceeds the GCN method in terms of accuracy, and the data enhancement technology further improves the accuracy of the proposed approach.

5.5 Summary

In this chapter we have examined the use of the TDGNN in food recommendation to improve recommendation accuracy. By means of data augmentation, a new strategy has been proposed to convert the recommendation task into the predicting problem of unknown node connections in the graph. The prediction accuracy has been enhanced by considering users' temporal behaviors into the network. Experimental results have shown the superiority of the proposed approach over traditional GNNs.

Chapter 6

Conclusions

Recommendation systems have been widely used in many areas, and have enjoyed notable success, especially in commercial applications. Research on food recommendations has become increasingly important over the past decade as it has direct relevance not only to quality of living but also personal health and wellbeing. In this thesis, our aim was to develop novel approaches that address the limitations of existing techniques and provide a balanced, personalized, and accurate way of recommending food to users. To achieve this aim, we formulated three specific objectives, each addressed in a separate chapter.

Chapter 3 presents a many-objective optimization-based recommendation approach that optimizes four objectives simultaneously: user preference, user diet pattern, food nutritional values, and food diversity. This approach is designed to provide personalized recommendations that balance the nutritional value and diversity of food items, while also accommodating individual dietary preferences.

Chapter 4 proposes a sequence-based recommendation model that utilizes long short-term memory networks and a collaborative filtering unit to consider the dynamically changing user behavior. This model takes into account the temporal dynamics of user preferences and aims to provide accurate recommendations that are tailored to each user's current food preferences.

Chapter 5 explores the use of graph neural networks and data augmentation techniques to generate a temporal-dependent graph for predicting unknown connections. This approach is designed to leverage the underlying structure and dynamics of food consumption patterns to provide personalized and accurate recommendations.

In this chapter, we summarise the achievements made from the research carried out in this thesis in Section 6.1 and outline the future work in Section 6.2.

6.1 Summary of achievements

Chapter 3 is devoted to solving the food recommendation problem based on many-objective optimization (MaOO). Not all food recommendation problems can be best addressed by such classical recommendation techniques such as the content-based, collaborative-based and hybrid methods. A novel MaOO-based recommendation approach has been developed to provide a balanced and systematic way of performing food recommendation tasks. Four crucial objectives, the user preference, user diet pattern, food nutritional values and food diversity, have been simultaneously optimised in the proposed recommendation framework.

Three Pareto-based algorithms have been involved in addressing the challenging recommendation task, and comprehensive experiments based on real-world data sets have been conducted to verify the effectiveness of the proposed MaOO-based recommendation framework. Convergence and diversity are the two most widely-used to evaluate the performance of MaOO algorithms where convergence evaluates the approximation of the experiment results to the Pareto optimal front, and diversity is used to evaluate the distribution over the Pareto front. It is shown that the new recommendation approach provides a more balanced way of recommending food than the classical recommendation methods that only consider individuals food preferences.

In Chapter 4, we consider the sequentially ordered information from user-item interactions in recommendation systems where a sequence-based recommendation model is put forward with applications to the food recommendation scenario. In many application domains, interactions between users and items are more likely to be dynamic rather than static, and thus dynamic user behaviours need to be taken into account in order to make more accurate recommendations. In this chapter, the long short-term memory networks are employed as the building block to establish such a recommendation model, and a collaborative filtering unit is adopted to make personalized food recommendation.

Extensive experimental results on real-world data sets have demonstrated a remarkable improvement of the proposed method in food recommendation over some widely used recommendation approaches, including Item-KNN, Prod2vec, and Caser. Several metrics such as precision@N, recall@N, mean average precision (MAP), as well as mean reciprocal rank (MRR) are used to evaluate the performance of the proposed method against those baseline techniques, showing early promise of the proposed sequence-based recommendation approach.

In Chapter 5, we explore Graph neural networks (GNNs), one of the most advanced neural networks that has found wide applications in various fields including chip design, problem reasoning, and traffic flow prediction for food recommendation systems. When applying GNNs to recommendation systems, a common approach is to generate a bipartite graph to describe the user-item interactions due to its capabilities of accurately making predictions about unknown connections and efficiently learning the underlying patterns and relationships between the nodes in the graph. In this chapter, we propose a new strategy using the temporal dependent GNNs and the data augmentation technique that converts the recommendation task into a predicting problem of unknown node connections in the graph.

We have conducted computational experiments to evaluate the proposed model against graph convolutional networks (GCNs) model, which is the most representative GNNs-based learning technique. The GCNs leverage a localized, initial estimate of spectral graph convolution to learn node representation efficiently. We compare the performance of the two methods with and without data augmentation. Experimental results on real-world data sets have demonstrated the superiority of the proposed strategy over the GCNs.

6.2 Future work

There are several lines of investigation for future work.

First, on the use of many objective optimisation for food recommendation it would be interesting to consider more user related objectives in the proposed MaOO model, given there have been many more considerations in the literature. More comprehensive experiments should be conducted on diverse food recommendation data sets. Other advanced machine learning techniques should be considered when analysing the food related time series data. Further research topics could include the extension of the main results reported in this thesis to more comprehensive systems using more the latest filtering algorithms.

Second, additional information such as images and reviews should be included in the design of food recommendation systems, which will have direct consequences on the type of the machine learning techniques to be used. When developing the sequence-based FSs, it is important to consider how to make the recommendations more personal and adapt to users particular taste and requirements. Furthermore, the proposed approach should be compared with more advanced machine learning techniques and explored for cross-domain recommendations.

Third, we should make the best use of GNNs to make food recommendations more robust and explainable. Incorporating GNNs into food RSs have enabled more accurate prediction of user preferences and better personalized recommendation as GNNs can effectively capture the semantic information and structure of the graph. To be more specific, GNN-based models can capture both structural connection and high-order similarity between users and objects, and the semantics is expanded that users with comparable interactions would have similar preferences through repeated instances of information propagation. However, more research is needed to optimise many competing and potentially conflicting objectives and give accurate, robust and personalised recommendations at the same time.

Last but not least, it is desirable to conduct a systematic study of food recommendation by integrating a variety of datasets on food, lifestyle, wellbeing, health, genetics etc over a long period of time in order to have a deep understanding of the key issues involved. Innovative machine learning and high-performance computing methods would be needed to effectively integrate and make sense of these inter-related data properly to obtain much needed knowledge about the relationship between food, lifestyle, generics and disease. The work described in the thesis is a step in this direction.

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