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Many-objective optimization meets recommendation systems: A food recommendation scenario

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ABSTRACT

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 paper 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.

1. Introduction

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 [48,49,1,50]. 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 [9], e.g. the development of certain chronic diseases such as cancer, diabetes and obesity [11]. 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 [10,23]. 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.

In order to solve this problem, the many-objective optimization (MaOO) algorithms have been introduced to the food recommendation field, where the original recommendation problem has been converted into an MaOO one. It should be noted that most MaOO-based recommendation studies have restricted themselves to the optimization of only two objectives (i.e. user preferences and food nutritional values) regarding the users' health needs, and this often leads to sub-optimal food 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 MaOO 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 MaOO model, which can bring high computation costs and great visualization difficulties [36,51].

In this paper, 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,

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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 paper 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 paper is organized as follows: Section 2 presents the related work about traditional food recommendation methods. Section 3 develops an MaOO model for food recommendation. Section 4 discusses the experimental results and the corresponding metrics chosen for algorithm evaluation. Section 5 presents some conclusions and future directions.

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 [12]. Note that food recommendation, as a special recommendation field, is different from its counterparts such as movie or e-commerce recommendation [43] 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 [33]. 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 [24]. 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 [32].

So far, very little work has been done on food recommendation under real-world settings [30]. 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 [46], 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 [47] 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 [45], 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) [24]. This motivates us to investigate more specialized MaOO algorithms that target at supplying users with better food recommendation plans.

3. A many-objective optimization model for food recommendation

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 [2]. The MFP data set provides 1.9 million records of meals recorded by 9.8 K MyFitnessPal users from September 2014 to April 2015 on 71 K food items.

Table 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

Table 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 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

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 2 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.

In Fig. 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 consumption frequency of 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.

3.2. Problem Formulation

3.2.1. User Preference

User preferences refer to the attitudes and preferences that individuals have toward foods [12]. 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 paper as a measure of correlation between two food items in the data set, as well as a qualitative measurement for evaluating food preferences [4]. We compute the correlation matrix using PPMI for all the foods in the MFP data set.

Objective 1: Maximize user preference

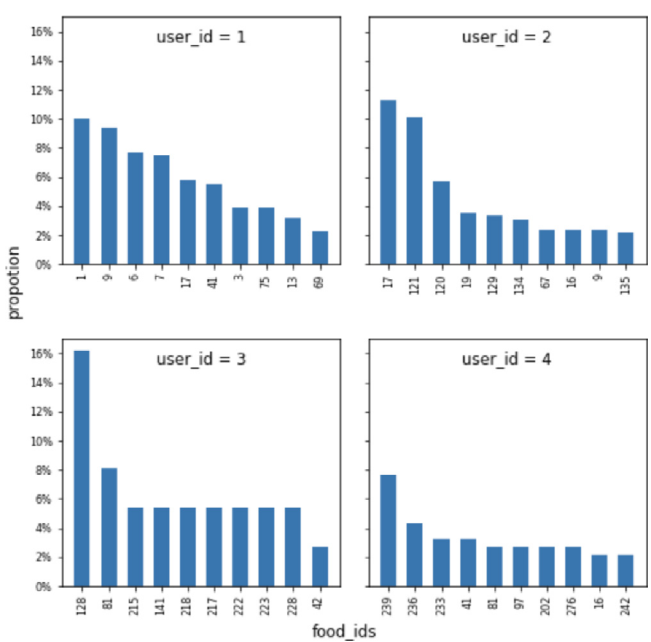

Fig. 1. Histograms of four users.

$$\mathrm{PPMI}(f_i, c_i) = \max\left(\log_2 \frac{P(f_i, c_i)}{P(f_i)P(c_i)}, 0\right) \tag{1}$$

where f_i and c_i denote the i-th food item in Table 2 and the i-th food context in Table 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 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 paper, the PPMI is chosen as the measure to assess users' food preference learning.

Table 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 Eq. (1). PPMI matrix is also used in the nutrition section to find healthier substitutes.

3.2.2. Nutrition

Malnutrition is associated with symptoms such as fatigue, dizziness, and even diseases [39]. 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

Table 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)	5 g per day (2 g per day)
Fruits and vegetables	400 g per day
Total dietary fibre	From foods
Non-starch polysaccharides (NSP)	From foods

Table 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

intake is identified as the primary cause of chronic metabolic diseases like obesity [34]. Table 4 provides information regarding the nutritional intake of users according to WHO guidelines.

Table 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 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.

Objective 2: Maximize S_i

$$S_i = |sp_i - 0.1| + |sp_i - 0.15| + |sc_i - 0.55| + |sc_i - 0.75| + |sf_i - 0.15| + |sf_i - 0.3| \tag{2}$$

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.

3.2.3. 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 [3]. 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

$$D = 1 - \sum_{i=1}^{n} P_i^2 \tag{3}$$

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.

3.2.4. 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 [37].

To measure changes in diet patterns over time, we chose Dynamic Time Wrapping (DTW) as an indicator, which is originally designed for comparing two time series of different lengths during the same time-period [38]. The primary reason for choosing DTW is that it can measure the similarity of two sequences of different lengths [40].

Objective 4: Maximize DTW

$$\mathrm{DTW}(i,j) = -\mathrm{Dist}(i,j) + \min[\mathrm{DTW}(i-1,j), \mathrm{DTW}(i,j-1), \mathrm{DTW}(i-1,j-1)] \tag{4}$$

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. An MaOO 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 [16]. In this paper, 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 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 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
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 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.

Table 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

Algorithm 2: Mating Selection

Require: $P \longleftarrow Fitness\_calculation(P)$
$Mutation(P)$
$Crossover(P)$
$P' \longleftarrow Tournament\_selection(P)$
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: Environment Selection

Require: $P' \longleftarrow Mating\_selection(P)$
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

4. Experimental results and evaluation

For performance evaluation, three typical MaOO algorithms, i.e. the SPEA2 [22], NSGA-II [7], and SPEA2 + SDE [25], 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.

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. 2–5 show that the Pareto-fronts optimization results of the three objectives, i.e. user preferences, nutrition scores and food diversity. Fig. 3 shows better convergence and diversity than Figs. 2, 4 and 5 for the fact that, the results in Fig. 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 the information (about the user's dietary preferences, nutritional intake, and dietary patterns) is fully extracted from the data set in Fig. 3. Meanwhile, food diversity is limited by the users' dietary range of choices in Figs. 2, 4 and 5. In summary, food diversity is an essential factor in guaranteeing individuals' health and should be considered and optimized simultaneously with other objectives.

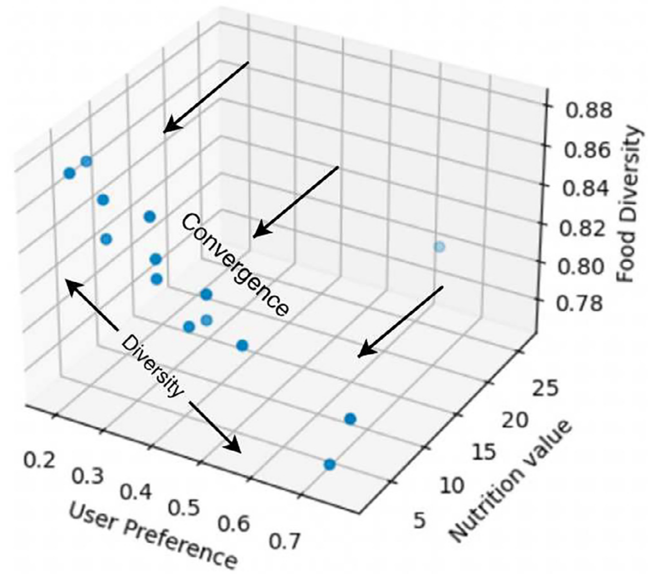

Fig. 2. Pareto-front of three objectives.

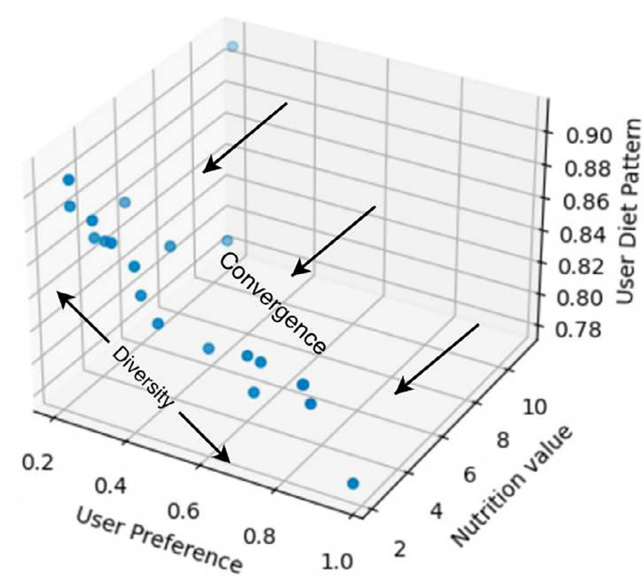

Fig. 3. Pareto-front of three objectives.

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. 6–8. Three kinds of user group sizes are set for evaluating the convergence and diversity of these algorithms. It is found that Fig. 5 shows better convergence performance due to the density of the intersection of lines located on small range of the objective value.

4.3. Performance Comparison

Many metrics are put forward to evaluate the performance of MaOO algorithms, where convergence and diversity are the two

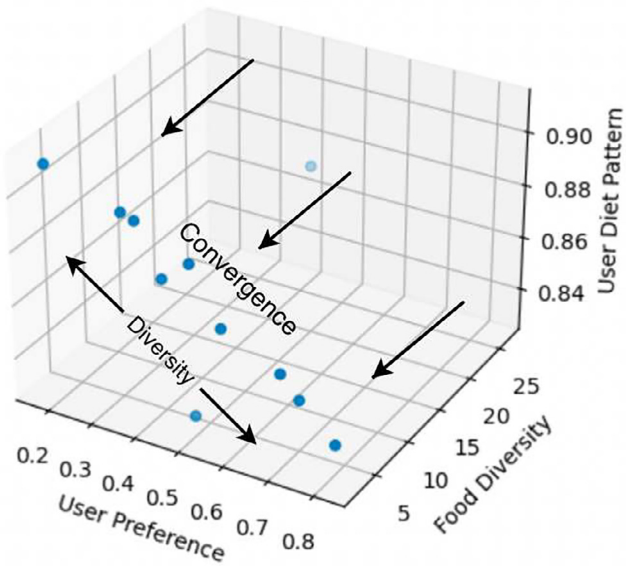

Fig. 4. Pareto-front of three objectives.

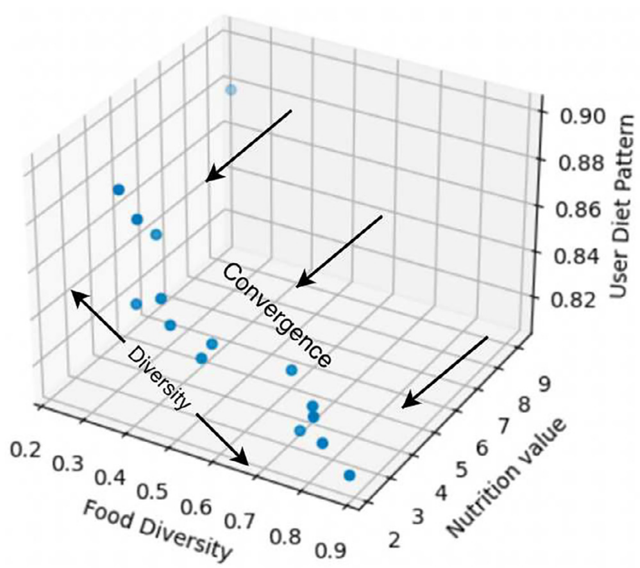

Fig. 5. Pareto-front of three objectives.

most widely-used ones. Convergence evaluates the approximation of the experiment results to the Pareto optimal front, while diversity is used to evaluate the distribution over the Pareto front [6,44]. In this paper, the hypervolume is used as the performance metric and it has the advantage of being fully in line with Pareto dominance [41]. 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:

$$H(S) = \Lambda(\{q \in \mathbb{R}^d | \exists p \in S : p \leqslant q \quad \text{and} \quad q \leqslant r\}) \tag{5}$$

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.

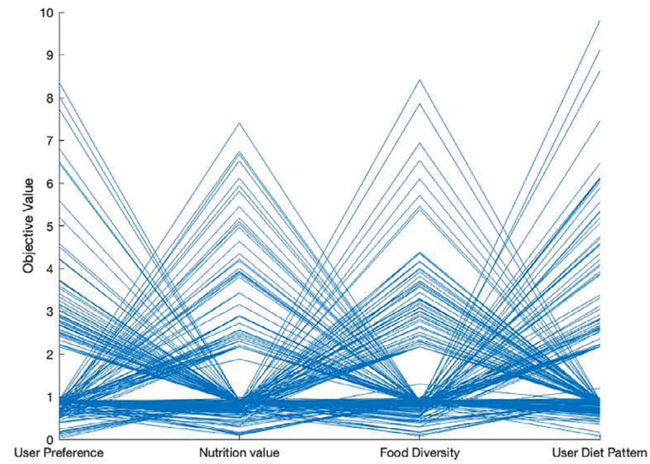

Fig. 6. Average of one user on four objectives.

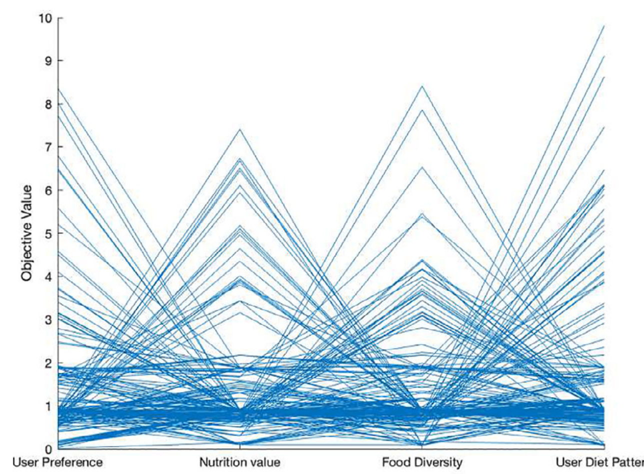

Fig. 7. Average of five user on four objectives.

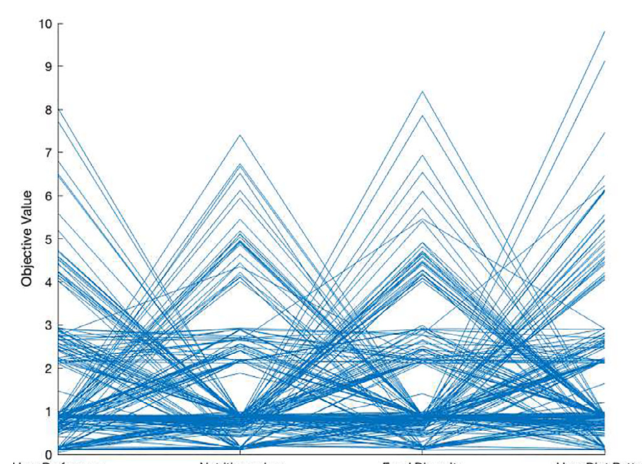

Fig. 8. Average of ten user on four objectives.

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

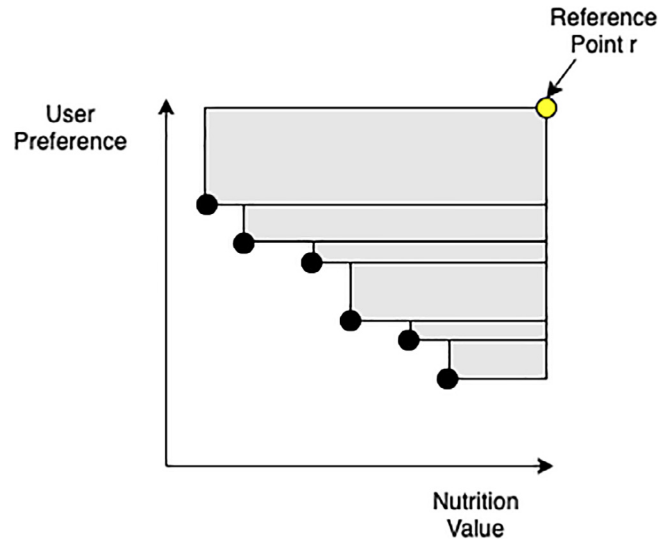

Fig. 9. Hypervolume illustration.

Table 6
Comparison of three MaOO algorithms' experimental results.

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

As it is difficult to illustrate the hypervolume indicator in four or more dimensions, Fig. 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 paper has chosen the reference point by 1.1 times the biggest value of every objective based on common practices [26]. 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 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.

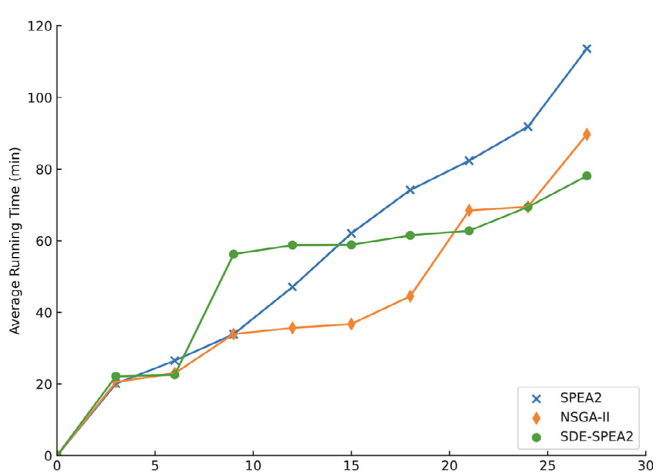

Fig. 10. The performance of different algorithms with different user group size.

Fig. 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.

5. Summary & Contributions

In this paper, 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 paper to more comprehensive systems using more up-to-date filtering algorithms [17,15,27,28,31,52,8,53,19,18,21,5,14,13,42,35,29,54,20].

CRediT authorship contribution statement

Jieyu Zhang: Data curation, Conceptualization, Methodology, Writing - original draft, Software. **Miqing Li:** Methodology, Software. **Weibo Liu:** Visualization, Investigation, Writing - review & editing. **Stanislao Lauria:** Writing - review & editing, Formal analysis. **Xiaohui Liu:** Validation, Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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