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Corpus Construction for Automatic Meal Planning

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Abstract

Eating a healthy diet every day is ideal, but difficult for many people. There is a scarcity of information and available resources regarding ideal food combinations, limiting the possibility of developing effective solutions for culinary information processing. As a result, food recommendations based on existing data tend to be unhealthy because the majority of users lack nutritional knowledge. While collecting healthy and tasty menus through crowdsourcing is one solution, such data-input tasks must be carefully designed from a combinatorial perspective. We describe a methodology to operationalize the collection of appropriate data for this complex task, present notable features of the resulting data resource, and illustrate how the obtained data can be referenced in automatic menu planning.

Keywords: combinatorics, culinary information processing, nutrition

1 Introduction

In recent years, research in culinary information processing has been intensively explored in food recommendation [1, 2, 3]. From the nutritional perspective, there is research interest in personalized nutrition [4], dementia prevention [5, 6], and healthy aging [7]. While artificial intelligence (AI) tools [8, 9, 10] are gaining attention for such purposes, obtaining large volumes of high-quality training data remains a significant challenge. There are two main reasons for this lack of data, as described below.

1.1 Misinformation on Nutrition

Nutritional recommendations are often changed due to newly discovered issues. For example, a globally influential diet proposed an animal-to-plant (A:P) protein ratio, then revealed its inadequacy in essential micronutrients [11]. In some countries, regulations have been implemented to prevent excessive weight loss in fashion models. However, there are no such regulations in Japan, and ultra-thin fashion models have a negative influence on healthy teenagers [12]. Meanwhile, a new problem has been discovered in Japan: the obesity rate among young women is rising [13]. The MHLW (Ministry of Health, Labour and Welfare,

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Table 1: An example of meal planning

Menu	Main dish					Side dish						Soup dish			
	X1	X2	X3	X4	X5	Y1	Y2	Y3	Y4	Y5	Y6	Z1	Z2	Z3	Z4
A	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0
B	n/a	1	0	0	0	n/a	n/a	1	0	0	0	1	0	0	0
C	n/a	n/a	1	0	0	n/a	n/a	n/a	1	0	0	n/a	0	0	0
D	n/a	n/a	n/a	0	1	n/a	n/a	n/a	n/a	0	1	n/a	0	1	0

Japan) used to recommend eating 30 different foods a day [14], which was later found to be associated with overeating, and deleted. It is speculated that some healthy eating habits, including the Japanese diet, contribute to healthy aging [15, 16, 17]. However, the definition of the Japanese diet is reported to be ambiguous [18]. A survey separate from the national survey found that many Japanese subjects should improve their nutrient intake [19]. Another study suggested that people who eat out a lot tend to be unhealthy [20]. There are restaurant owners who believe a healthy diet will lead to unsuccessful business [21]. Alternative diets, such as the Mediterranean diet, are thought to be healthy; however, there is still a lack of research on what constitutes a healthy diet for older adults [22].

1.2 Ideals vs. Reality

Ideally, meals should be both tasty and healthy (positive-positive). In reality, however, meals often result in either (1) tasty but unhealthy meals (positive-negative) or (2) unappetizing and nutritious meals (negative-positive). Finding the right balance between taste and nutrition requires a lot of computational thinking (such as, efficient calculations, boolean search). Since such information processing is very difficult for humans, it requires computer assistance. Currently, we do not have the data to develop practical tools. Solving this ”bootstrap problem,” which involves generating initial high-quality data, is essential to advancing automatic meal planning [23, 24, 25].

2 Methodology

To address the current problem, we designed a meal planning task. The task is basically a card sorting task [26, 27] to gain insight into how people understand food items. Table1 shows an example of meal planning. In the example, the number of main, side, and soup dishes are five, six, and four, respectively. The bit ‘0’and ‘1’ indicates the dish was not selected and selected, respectively. The abbreviation n/a means the item is no longer available as it is already selected in previous menus. A worker in the task has created the four menus (A, B, C, and D) using 11 dishes in this example.

For feasibility, it is important to control the number of item combinations. If there are too few items, a satisfactory menu would not be created. However, if items are too many, the number of combinations will be too large. For example, if there are 33 items to choose from, then the number of ways to choose one or more items is $(2^{33}) - 1 = 8,589,934,591$. On the other hand, if the items are divided into several categories (e.g., main dishes, side dishes, soup dishes) and the number from each category has upper and/or lower limits, the number of combinations can be kept within a realistic range. Then, the resulting dataset

Table 2: Instructions to crowd workers for creating the 4-menu meal plan

Rule	Description
#1	There must be one main dish for each menu.
#2	There must be one or more side dishes for each menu.
#3	The number of soups for each menu must be zero or one.
#4	The same dish must not be selected for multiple menus.
#5	There must be six or more different ingredients for each menu.
#6	The menus must (a) include varied ingredients, (b) be colorful, and (c) look tasty.

Table 3: How many menus were created? And, how many dishes were chosen?

Gender	Age of the people					tot.	Unique number of dishes			
	20s	30s	40s	50s	60s		Main	Side	Soup	All
Male	4	104	240	100	0	448	127 / 144	168 / 180	71 / 72	366 / 396
Female	56	156	228	68	4	512	129 / 144	175 / 180	71 / 72	375 / 396
tot.	60	260	468	168	4	960	138 / 144	178 / 180	72 / 72	388 / 396

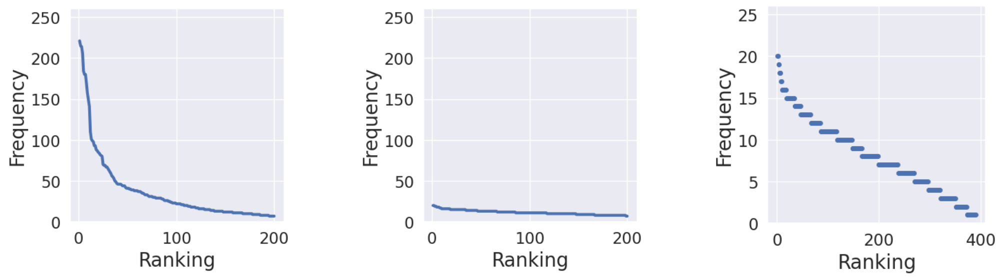
is expected to be of high quality and concise, since useless combinations (e.g., overeating menus) are excluded.

3 Corpus Construction

To put the methodology into practice, we used a crowdsourcing platform,[1] and the instructions presented in Table 2 were given to the workers to make the input data reasonable. For this task, we referred to the book "My Menu Diary" [28] published by a Japanese actress. Because the author was such a gourmet, the menus in the book are all appetizing. Also, they are healthy as the following suggestions are reflected: (1) SMS meals (menus consisting of a staple food, a main dish, and side dishes) [29] are good for nutrition intake, and (2) a diet rich in fruits and vegetables [30], and fermented foods, can promote the health of the gut microbiome [31, 32] and may help promote healthy aging.

We prepared 12 tasks using 396 different dishes introduced in the book. Each task corresponds to each month (from January to December). The crowdsourcing workers were presented with 33 seasonal dishes (12 main, 15 side, and 6 soup dishes) for each month. In each task, 20 workers participated in and four different menus were created by each worker. As a result, 960 menus in total were obtained, as shown in Table 3. The number of non-duplicate menus was 911. The number of non-duplicate workers was 57. There were 39 duplicate menus that were entered by two or more non-duplicate workers. The menu most frequently entered was a combination of curry rice and vegetable salad, and six workers chose this simple combination of the two dishes. While some dish items were entered by multiple workers, some were not entered by anyone. The right side of Table 3 shows the number of main, side, and soup dishes selected in the task. Six main dishes and two side dishes were not chosen by anyone, and there were a total of eight dishes with a frequency of zero. (Parenthetically, the dishes with zero frequency were rare dishes. This suggests

[1] `https://crowdworks.jp/`



(a) Ingredient Top200 (b) Dish Top200 (c) Dish ALL

Figure 1: Relationship between item ranking and frequency

Table 4: Stirling numbers of the second kind, $S(n,k)$

$n \backslash k$	0	1	2	3	4	5
0	1	n/a	n/a	n/a	n/a	n/a
1	0	1	n/a	n/a	n/a	n/a
2	0	1	1	n/a	n/a	n/a
3	0	1	3	1	n/a	n/a
4	0	1	7	6	1	n/a
5	0	1	15	25	10	1
...				...		
14	0	1	8,191	788,970	10,391,745	40,075,035
15	0	1	16,383	2,375,101	42,355,950	210,766,920

that some delicacies favored by a particular Epicurean may not be to everyone's favorites.)

The ages of the workers who participated in the menu planning task ranged from their 20s to their 60s. Regarding age group, the largest number of participants, both male and female, were in their 40s. It is reported[2] that crowdsourcing workers tend to be in their 40s. This trend was consistent with the workers in our tasks.

In the task, the dishes to be selected were presented as specific dish items, and duplicate selection of the same dish item in the same meal plan was prohibited. On the other hand, there were no restrictions on the ingredients for cooking the dishes, and participants were to write what ingredients they wanted to use. To be more specific, for the ingredients in each menu, we asked workers to enter text using their mental lexicon rather than presenting them with a long list of foods used in home cooking. As a result, there was a larger difference between the head and the tail in the long tail phenomenon [33] for ingredients than for dishes. The top 200 most frequently chosen ingredients and dishes are shown in Figure 1 (a) and (b). Since the dishes were selected from the dish choices, the item frequencies ranged from 1 to 20, based on the selection of the 20 workers, as shown in Figure 1 (c).

By dividing dish items into categories for the constraints of not overeating, the total number of possible item combinations is reduced. Also, the four menus in a meal plan must not be overlapped with each other. For choosing four from 12 main dishes, the number of combinations is ${}_{12}C_4 = 495$. For four menus, choosing none or one from six soup dishes,

[2] `https://www.meti.go.jp/policy/sme_chiiki/town_planning/machigenki/column/09_tanaka.pdf`

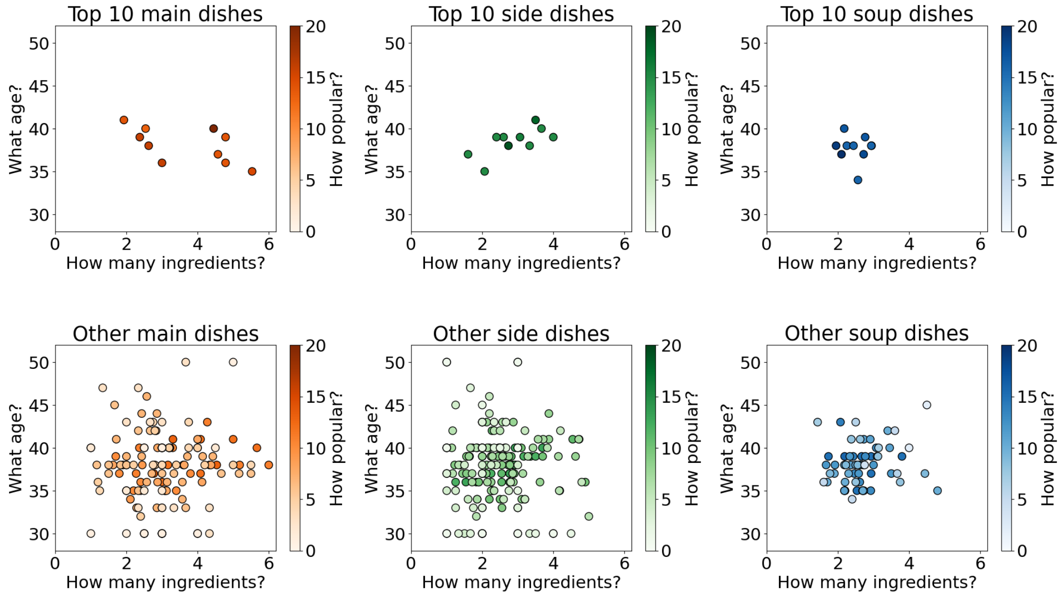
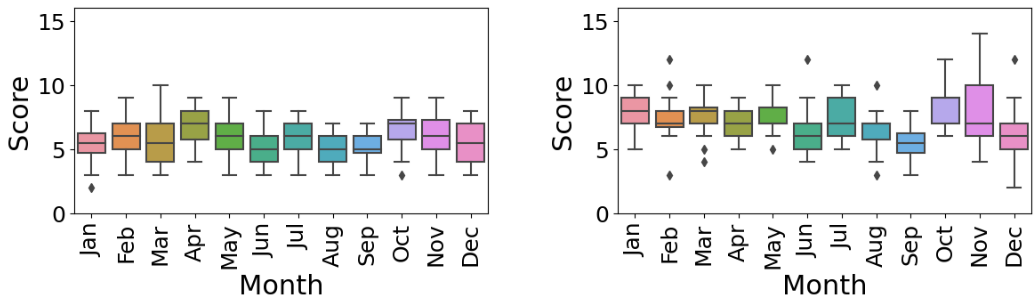


Figure 2: The correlation among the number of ingredients, the average age of people, and popularity of dishes.

the number of combinations is ${}_6C_0 + {}_6C_1 + {}_6C_2 + {}_6C_3 + {}_6C_4 = 57$. For four menus, choosing one or more from 15 side dishes, the number of combinations is $S(15,4) = 42,355,950$, which is calculated as shown in Table 4. Here, $S(n,k)$ is called Stirling numbers of the second kind, and gives the number of combinations that divide n identified elements into k groups [34]. The numbers are obtained by the following recurrence formula. For any natural number n, $S(n,1) = 1, S(n,n) = 1$. And, $S(n,k) = S(n-1,k-1) + kS(n-1,k)$ for any $n,k(k \geq 2, n \geq k+1)$. Since the choices of the main, side, soup dishes are independent, we multiply the values together: $495 \times 42,355,950 \times 57 = 1,195,073,129,250$. As can be seen, the obtained number of combinations is smaller than the number of combinations obtained without any constraints.[3] In addition, the number of ingredients in a menu must be more than six, and people have varied preferences for eating habits. Depending on people's tastes, they may want to include some of the 15 side dishes in the meal plan, not all of them. Therefore, the actual number of combinations for the ideal menu planning is likely to be smaller than the calculated number of dish combinations explained above. This suggests that by more accurately predicting human biases in food selection, knowledge discovery for automatic meal planning could get closer to the ideal.

To visualize the workers' preferences inherent in the corpus of the meal plans, Figure 2 shows the correlation between the average number of ingredients, the average age of the workers, and how many workers chose the dishes. The scatter plots in the first row present the top 10 most popular common dishes that can be easily found through a quick web search. The scatter plots in the second row present other dishes that are associated with a variety of dish choices for ideal meal planning. While these dish choices contain useful knowledge for optimal menu planning, how to discover such knowledge automatically is non-trivial, as tasty and healthy menu creation is not yet supported by web search or generative AI. In the figure, the top five main dishes (five darkest orange dots in the gradation) were high-

[3] Specifically, $((2^{33}) - 1)^4 = 8,589,934,591 \times 8,589,934,591 \times 8,589,934,591 \times 8,589,934,591$



(a) GPT-4o

(b) Gemini 2.5 Pro

Figure 3: Evaluation of meal plans generated by ChatGPT and Gemini

calorie dishes (curry rice, beef steak, pork cutlet, fried horse mackerel, tempura). They are followed by healthier, lower-calorie dishes. For healthy eating habits, portion sizes of high-calorie dishes should be carefully considered. With these exceptions, the resulting dataset can be used for a knowledgeable dataset in tasty and healthy meal planning because the obtained food combinations manifest the realistic preferences of people (age, ingredients, popularity shown in Figure 2).

4 Automatic Meal Planning

Automatic menu creation was explored using generative AI, specifically the GPT 4o[4] (GPT) and Gemini 2.5 Pro[5] (Gemini) models. The constructed corpus of meal plans was used as reference data and evaluation data. Each of the generative AI models was prompted with instructions to create meal plans (specifically, the same instructions as those given to the original crowd workers (Table 2) were used). Since neither the human nor the AI model was given any concrete example menus, the automatic meal planning was performed through complete zero-shot learning. When crowd workers did not understand a rule, they asked questions to clarify it. On the other hand, AI models simply ignored rules when they did not understand the meaning or importance. To address this issue, data from the crowd workers was used as a reference for sanity testing. Specifically, the meal planning rules were repeatedly explained to the AI models through interactive conversations until they stopped ignoring the rules and generated meal plans indistinguishable from those of the crowdworkers.

In the beginning, Rule#6 in Table 2 had been ignored by the AI models. When they were told not to ignore the rule, Rule#1 to Rule#5 were ignored. Also, (a), (b), and (c) in Rule#6 had been treated as mutually exclusive conditions. When they were told to make it more colorful, they included more green ingredients. When they were told to include varied ingredients, they forgot about harmony in the menu. Then, they created unappetizing combinations of dishes. After the models understood all of the rules properly, they started creating meal plans that were similar to those by the crowd workers.

The meal plans created by generative AIs were evaluated by using the constructed corpus. Specifically, meal plans were scored according to how many dishes matched the

[4] https://platform.openai.com/docs/models/gpt-4o
[5] https://cloud.google.com/vertex-ai/generative-ai/docs/models/gemini/2-5-pro

Table 5: The number of dishes in the 4-menu meal plans created by the crowd workers

	By the month												ALL
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	
Min.	10	9	9	10	12	11	11	10	10	11	10	10	9
Max.	18	16	17	16	18	17	18	18	14	17	16	20	20
Avg.	13.15	12.35	12.85	13.10	13.35	12.70	13.90	13.75	12.20	13.65	13.00	12.60	13.05

worker's choices of dishes. If there was a matching dish, it was given 1 point. Then, the total points were used as the score for each of the AI models. The results are presented in Figure 3. The average scores of GPT and Gemini were 5.81 and 7.15, respectively. The difference was significant at $p < 0.001$ using a paired t-test. While the response time of GPT was shorter than Gemini, the quality of the result by GPT was overall inferior to that by Gemini. For example, the most popular main dish, curry rice, which was chosen by the all 20 workers, was not included in the meal plan by GPT, while Gemini included it. An ideal menu plan is achieved by (a) combining delicious dishes, and (b) a wide variety of nutritionally balanced dishes. While a meal plan with a large number of dishes tends to be more ideal (healthier and more appealing to diners), it can be more difficult to examine food combinations. Therefore, a meal plan can be evaluated using the number of dishes as a measure of excellence. Table 5 shows the minimum, maximum, and average number of the dishes in the meal plans created by the worker. Those numbers in Gemini's meal plan were 12, 17, and 14.67, respectively, while those of GPT's meal plan were 11, 13, and 11.75, respectively. On average number of the dish choices, GPT underperformed the workers, and Gemini outperformed the workers. The differences were significant at $p < 0.001$ using a paired t-test. Gemini was able to create delicious and nutritious meals as well as many workers, and in some cases better than workers. However, it cannot overcome the best meal planner among the workers, who included 20 dishes in an appetizing and nutritious meal plan. It is necessary to consider using the constructed corpus to create even better automatic menu planning.

5 Conclusion

We have presented a bootstrapping solution for automatic meal planning. A delicious and healthy diet is ideal, but difficult to put into practice. Therefore, we do not have existing data for training the AI models. In this study, we presented a methodology for constructing a corpus of initial small-scale menu plans through crowdsourcing. Then, we attempted to use it as a reference and evaluation dataset for automatic meal planning by the latest generative AIs. In our future research, we aim to develop a method for how to train the generative AIs so that they can surpass excellent menu creators.

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