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Exploration cycle finding a better dining experience: a framework of meal-plates

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Abstract

This study aimed to help people select an appropriate plate to enhance the quality of their dining experiences. Meals are not only a means of nutritional intake but also one of the "experiential contents" that enrich our daily lives. The attractiveness of a meal as an experience derives not only from the taste of the food, but also from its appearance, which includes the novelty of the ingredients and cooking methods, as well as presentation methods such as serving and coloring. The appearance of a dish is significantly influenced by its appearance and the plates on which it is served. Focusing on the point that "the plates enhance the attractiveness of the meal," we attempted to develop plate recommendation methods to improve the quality of the dining experience. The selection of serving plates should consider the compatibility of the plates and the consistency of the plate with the other plates served together. Although qualitative criteria exist for these factors, no unique correct solution exists, which renders plate selection difficult. Enabling computers to understand and process these criteria will provide support for plate selection in line with human cognition. We assumed that two elements were necessary to support plate selection to improve the quality of the dining experience (QoD): "understanding the characteristics of each meal and plate, as well as the appropriate combination of both" and "reflecting user preferences." Thus, this study proposes the "meals—plates cycle" as a framework that satisfies the aforementioned two elements. This paper presents the design guidelines for the framework, data construction based on the guidelines, and the development of elemental technologies.

Keywords: Exploration search; Dining experience; Plate selection

1. Introduction

Dining is one of the "experiential content" that enriches our daily lives, in addition to being a way to intake nutrition. The attractiveness of dining as an experience is highly related to dining presentation, such as the novelty of

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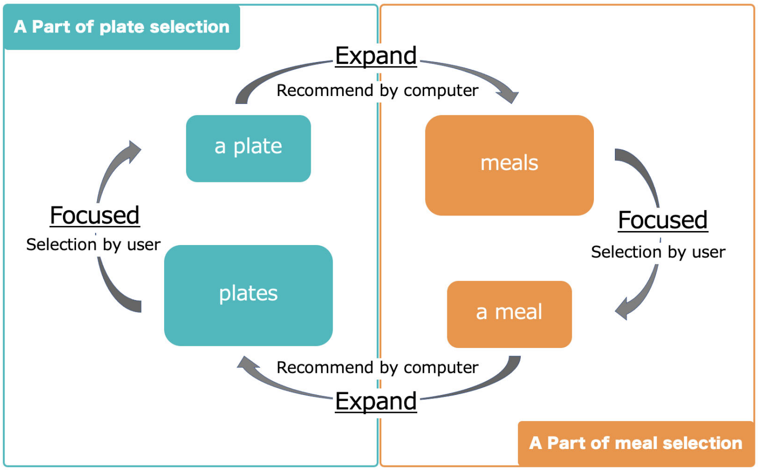

Fig. 1. Schematic of the search path of a user following a cycle. The cycle consists of an Expand part and a Focus part. The Expand part allows the user to gain knowledge of the characteristics and combinations of meals and plates. The Focus part allows the user to understand and reflect on his/her preferences.

meal ingredients, cooking methods, serving[8][17], and coloring techniques, rather than merely the deliciousness of meals[18].

The plates univocally are ”containers for serving meals” and are almost indispensable for serving meals. However, plates also have roles such as “making the food look attractive,” “symbolizing the place, scene, and value of the meals, and to whom the meals are served,” and “varying the taste and increasing the appetite[3][12][11]”.

The same meal appeared to be slightly different when the plates were changed. This is expected to help people enjoy their daily meals by eliminating their eating ruts. This is not only for the eater but also for the person who selects the plates, because he/she can enjoy the pleasure of coordinating the dishes by changing the plates. As these suggest, the plate plays more than a container for serving meals, and the plate selection significantly improves the dining experience. Therefore, we focused on selecting appropriate plates to improve the quality of the dining experience.

Harmonizing plates with meals is important to improve the quality of dining experiences. Regardless of the deliciousness of the meal, it will not appear good if it does not match the plates, and the entire meal will be less appealing. In addition, even if the plate looks beautiful and does not match the meals, the QoD becomes less attractive.

Multiple meals are often served on multiple plates. When serving multiple meals on multiple plates, consistency with other plates should also be considered. Qualitative criteria and findings regarding plate-and-meal combinations exist. However, no clear standards exist for an appropriate combination of meals and plates. Additionally, users must select plates based on their inspirations and preferences. Plate selection is a difficult problem that must satisfy constraints such as compatibility with meals and improvement in sensory evaluation, such as inspiration and preference. Therefore, we considered two essential elements “understanding the characteristics of each meal and plate, as well as the appropriate combination of both” and “reflection of user’s preference.”

This study aims to enable users to select a plate that enhances their QoD. To achieve this, it is necessary to satisfy the aforementioned two elements and understand the plates that enhance one’s own QoD by using various plates and repeating trial and error several times. We consider that this can be acquired during the exploratory search[6][15][16] process.

This study proposes a novel framework, the “meals–plates exploration cycle.” Target users of this framework are those who are not satisfied with their current plate and users who want to enjoy their meals more. The specific situation in which this framework will be used is when purchasing a new plate. In the “meals–plates exploration cycle,” the computer suggests several possible meals/plates for a single plate/meal, and the user selects one based on his/her preferences. The user follows this cycle for each plate or meal, and can find and deepen their understanding according to their own QoD. This paper discusses the framework design, data building, and underlying technology based on the framework design.

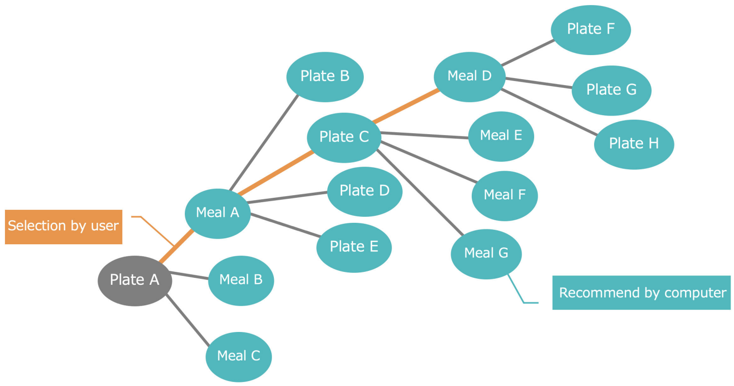

Fig. 2. Search paths for users following the cycle. Orange edges represent the user's selection path. The green nodes are the suggested plates and meals to be recommended by the computer. The user establishes his/her preferences by noticing multiple possible plates/meals.

2. "Meals–plates exploration cycle"

This section describes the design of the "Meals–plates exploration cycle" and its expected user interactions.

2.1. "Meals–plates exploration cycle" design

As mentioned in Section 1, two factors must be considered when selecting a plate to enhance QoD. The first is "understanding the characteristics of each meal and plate, as well as the appropriate combination of both," and the second is "reflection of user's preference." In addition, when a user selects a plate that enhances their QoD, they need to use various plates many times, repeating the trial and error process to understand the plate that enhances their QoD. Therefore, we propose a "meals–plates exploration cycle" as a novel framework that enables users to gain knowledge and deepen their understanding of their QoD while satisfying the two elements.

Figure1 illustrates the design of the meal–plate cycle. This cycle consists of an expanded and focused phase. The expanded phase corresponds to "understanding characteristics of each meal and plate, as well as the appropriate combination of both," and the focused phase corresponds to "reflection of user's preference." In the focused phase, the user selects one of several meals/plates recommended in the expanded phase. The meal-focused phase uses conventional recipe recommendation techniques based on meal similarity [14], ingredients [19], and preferences [2] to filter plates according to user intentions and preferences. The plate-focused phase can filter plates based on their appearance characteristics (e.g., color, pattern, shape, and size) according to the user's intentions and preferences. At this point, the user can select the meals/plates in the focused phase based on the recommendation of the expanded phase, which is the next phase in the process. In the focused phase, the computer recommends multiple meals/plates per plate/meal. The design of meal and plate relationship is described in Sections3.

To realize this cycle, a relationship between meals and plates must be established by identifying the conditions that should be met by the appropriate plates/meals for the meals/plates.

2.2. Expected "meals–plates cycle" interaction

Any of the four points "a plate," "plates," "a meal," and "meals" can be the exploration starting point. Figure2 shows an example of an assumed user exploration path starting from "a plate." When a cycle starts with a particular plate, the computer suggests several possible meal names to the user. The user then selects a meal name from the suggested meal names. From the meal selected by the user, the computer then proposes several plates.

Users can discover new meals or plates during exploration. The expanded phases that proposes multiple selections, helps the user expand the range of meal and plate selections without being limited by selection criteria and constraints based on the user's previous knowledge and dining experience. When a new meal is proposed that the user has never previously cooked, it may motivate the user to attempt cooking it, leading to an increase in the meal repertoire.

Table 1. Part of the plate data set (Plate ID, Product URL, Product description and Size data)

Plate_ID	Product URL	Product description	Long side(cm)	Short side(cm)	Height(cm)
001	https://item.rakuten...	The PK500 series is said to be the 500th cut design invented in the early 20th century, which captivated the aristocracy of the time and made Bohemia's meticulous cuts famous, a popularity that has not changed...	17.5	17.5	3
002	https://item.rakuten...	Product Description "DANSK Arabesque Pasta Bowl, 1 pc." is a unique item that will be the star of your table in everyday life and at parties. The Arabesque series is unique among DANSK products and is painted stroke by stroke by skilled craftsmen...	20.5	20.5	5.5
003	https://item.rakuten...	Namako walls, a traditional Japanese technique of heaping up plaster, are incorporated into the striking beauty of the plates. The plates, which resemble walls shaped in the shape of auspicious wishes, add color and splendor to the dining table...	27	24	1.8

Table 2. Part of the plate data set (Plate ID, Shape data and Material data)

Plate_ID	Circles	Corners	Flowers	...	Ceramics	Porcelain	Glass	...
001	0	0	1	...	0	0	1	...
002	1	0	0	...	0	1	0	...
003	0	0	0	...	1	0	0	...

3. Design of relationship between the meals and the plates

To form a relationship between meals and plates, we assumed two steps: (1) converting meal information and plate information to machine-readable data, and (2) associating meal information and plate information converted to machine-readable data in (1).

3.1. Conversion of meals and plates information to machine-readable data

The plates have various parameters, such as width, height, material, production date, and producer. Considering the relationship with the meals, these can be organized into two aspects: the functional aspect of "whether the meal can be physically served on the plates" and the aesthetic aspect of "whether the plate enables the meals to appear beautiful and delicious and enhances its qualities." We defined size, shape, and material as parameters related to the functional aspect and color and motif related to the aesthetic aspect, and then organized them.

Size, shape, and material-augmented subordinate attribution. We created a "plates dataset" by manually photographing and recording the attribute values of 100 household plates. We defined five subordinate attributions of size: "height," "width," "height from the plane," "depth," and "rim width," and stored each measured value in the data set. The value for the plates without a "rim width" was null. We defined two subordinate attributions of shape: "the whole shape" and "the bottom shape." Small plates (used for kaiseki meals) for sharing, square plates, gratin plates, and bowls were defined as classification categories for the overall shape. Plates that were difficult to classify were classified as deformed meals. The shapes of the bottom surfaces were defined and classified as "curved" if they are curved with respect to the ground plane and "parallel" if they are parallel to the ground plane. We defined three subordinate attribution of material: "ceramics/Japanese ceramics," "lacquerware," and "glass."

In addition, we focused on plate information sold on e-commerce websites and extracted the value of each attribute from product descriptions and pictures. In total, 432 plates were collected. We defined three subordinate attributions of size: "the long side," "the short side," and "height from the plane" and stored each measured value in the data set.

Shapes were difficult to classify based on product descriptions; therefore, we classified them by analyzing the product pictures. The classification category is eleven, such as circles, corners, and flowers. Forty-two types of materials were classified into ten categories, including ceramics, porcelain, and glass. In addition to these, the product URLs are also included in the dataset. Table 1 shows part of the plate data set (Plate ID, Product URL, Product description and Size data). Table 2 shows part of the plate data set (Plate ID, Shape data and Material data).

We developed automated techniques for collecting size and material data using regular expressions and keyword matching.

Table 3. Data and data formats available for food and plate information on each of the e-commerce and cooking sites

Information Resources	Meal or plate information	Acquirable data	Data format
E-commerce websites	Meal information	Meal names	Text data
	Plate information	Plate pictures	Picture data
		Size, shape, material	Text data
Cooking websites	Meal information	Ingredients and cooking procedures	Text data
		Meal picture	Picture data
	Plate information	Plate picture	Picture data

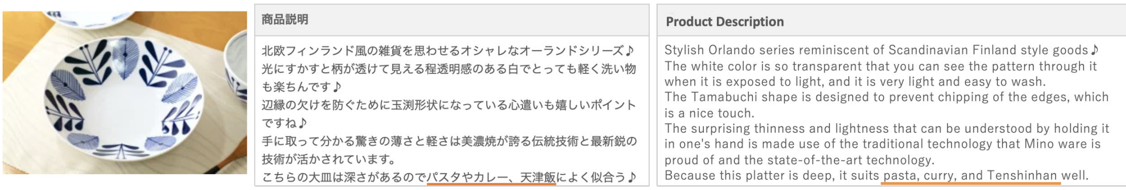

Fig. 3. Examples of meal names in product descriptions(Original text and first author's English translation)
Retrieved March 27, 2021, from Rakuten Ichiba Shopping Site (https://item.rakuten.co.jp/cera-pockke/da-0018/)

In this study, we used recipe data as cooking information. As recipe data, we used the Cookpad dataset [1], which is based on information from Cookpad, a recipe website to which users can contribute recipes. By characterizing this recipe data, the cooking information is converted into machine-readable information. In a study of structured cooking procedures, Mori et al. [9] proposed a method for generating flow graphs based on the Cookpad dataset. A flow graph in a cooking recipe is a directed graph that extracts the named entity of a cooking recipe (e.g., ingredients, cooking utensils, and cooking behavior) and represents the relationship between them. In this study, we deal with data tagged to these recipe terms (FG-dataset) to vectorize recipe features. The elements that can be extracted from the FG-dataset are directed relational data tagged to the unique expressions of a cooking recipe in terms of ingredients, recipe advice, cooking behavior, and cooking steps (FG-data). We extracted the named entity tagged with the ingredient tag (F) and the cooking behavior tag (Ac) together to create the FAcf vector. The vector is represented as a binary vector in which the presence or absence of each element is acquired.

3.2. Association of meals and plates information to machine-readable data

In this study, we considered that "e-commerce websites" and "cooking websites" could be used as resources containing both meals and plates information to map meals and plates information. We created relationships between meals and plates using two methods: e-commerce websites and cooking websites. In the method using only the e-commerce website, examples of meal names described in the product description of the plates were used as meal information, and the size, shape, and material attribute values of the plates with meal names included in the product description were used as plate information to construct a dataset associating them. The descriptions of plates sold on e-commerce websites mention the recommended meal names to be served on the plate. Figure 3 shows an example of meals mentioned in the product description of the plates.

For the method that uses only the cooking website, we proposed a method that uses machine learning to estimate the shape of the plate, flat or deep, based on vectorized meal ingredients and cooking behavior data. We also proposed a method for estimating a plate's shape, material, and taste using FastText text classification and shared recipe sentences as training data.

E-commerce and cooking websites combine the eating and drinking domains. However, this combination is not enough. This is because they have different purposes for disclosing and disseminating information. E-commerce websites have plenty of plate information, whereas cooking websites have a large amount of meal information. On e-commerce websites, plate size and materials are mentioned in detail in the product sentence and picture because of the purpose of selling products. However, meal information only includes the name of the meal in the product sentence. On cooking websites, the recipe category name, the recipe name, the ingredients included in the recipe, and the cooking

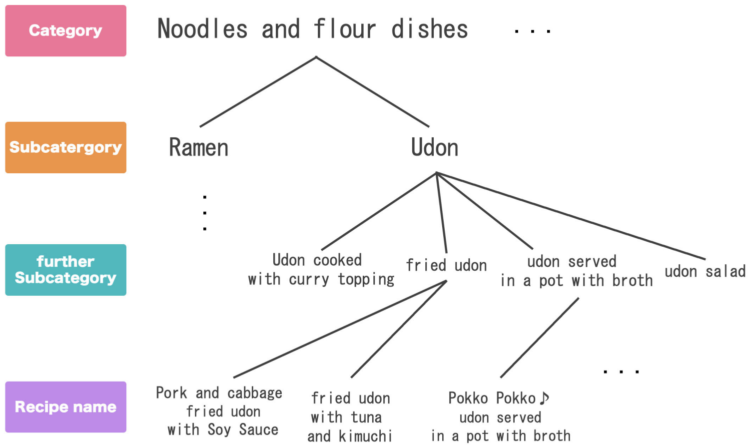

Fig. 4. Examples of Categorization

procedure are described in detail because of the purpose of publishing the recipes. By contrast, plate information is only a picture of cooked meals based on recipes. Cooking websites are available for more meals than e-commerce websites. This is because e-commerce websites use only the meals described in the product descriptions. In addition, recipes on cooking websites contain information such as meal materials and cooking methods, as well as meal names. Therefore, it also has the advantage of presenting a known plate for an unnamed meal if the ingredients and cooking behavior are similar to those of the named. Examples of unnamed meals include meals made from computer-generated recipes[5], meals made from leftover ingredients, and inventive meals. In a method that uses only cooking websites, collecting a large amount of information is challenging because of the need to manually collect plate information by viewing images. However, on e-commerce websites, both meal and plate information can be extracted from text.

As mentioned previously, both e-commerce and cooking websites have positive characteristics. E-commerce websites can extract information on meals and plates from text, whereas cooking websites have a wealth of information on meals. In this study, we proposed a method for constructing a relationship between meals and plates using both e-commerce and cooking websites, leveraging their positive aspects.

4. Development of relationships between meals and plates

The common item on e-commerce and cooking websites is the “meals name” in the extractable data organized in Section 3.

In this study, we considered that developing a relationship between meals and plates was possible through a common item, the “meals name.” On e-commerce websites, meal names are meal names as described in the product descriptions. On cooking websites, meal names are recipe categories and the recipe names. In this paper, we use “Rakuten Ichiba Dataset”[13] as the e-commerce website and “Rakuten Recipes” as the cooking website.

When forming a relationship between resources based on the meal name, it is necessary to follow two steps: “(1) understanding the names of meals in each resource,” and “(2) organizing the hierarchy of meal names among resources.” For understanding the names of meals on each resource in the case of the e-commerce website, clarification of the meal names that are present in the product descriptions is necessary because the plates are not categorized by meals name. Section5 describes a method for extracting meal names from product descriptions.

Creating a relationship between e-commerce and cooking websites is difficult because of the different granularities in the listed meal names. E-commerce websites are rough in granularity, whereas cooking websites are fine-grained. As mentioned in Section 2, cooking websites publish meal recipes with more detailed and structured names to enable cooks to filter their meals. Figure4 shows an example of the categorization of a recipe site. Because an e-commerce website is intended to sell products, it is considered that the meal names with a coarse granularity are listed to encourage purchasing by showing that the plates can be used in various meals. In Figure4, most meal names belong to the

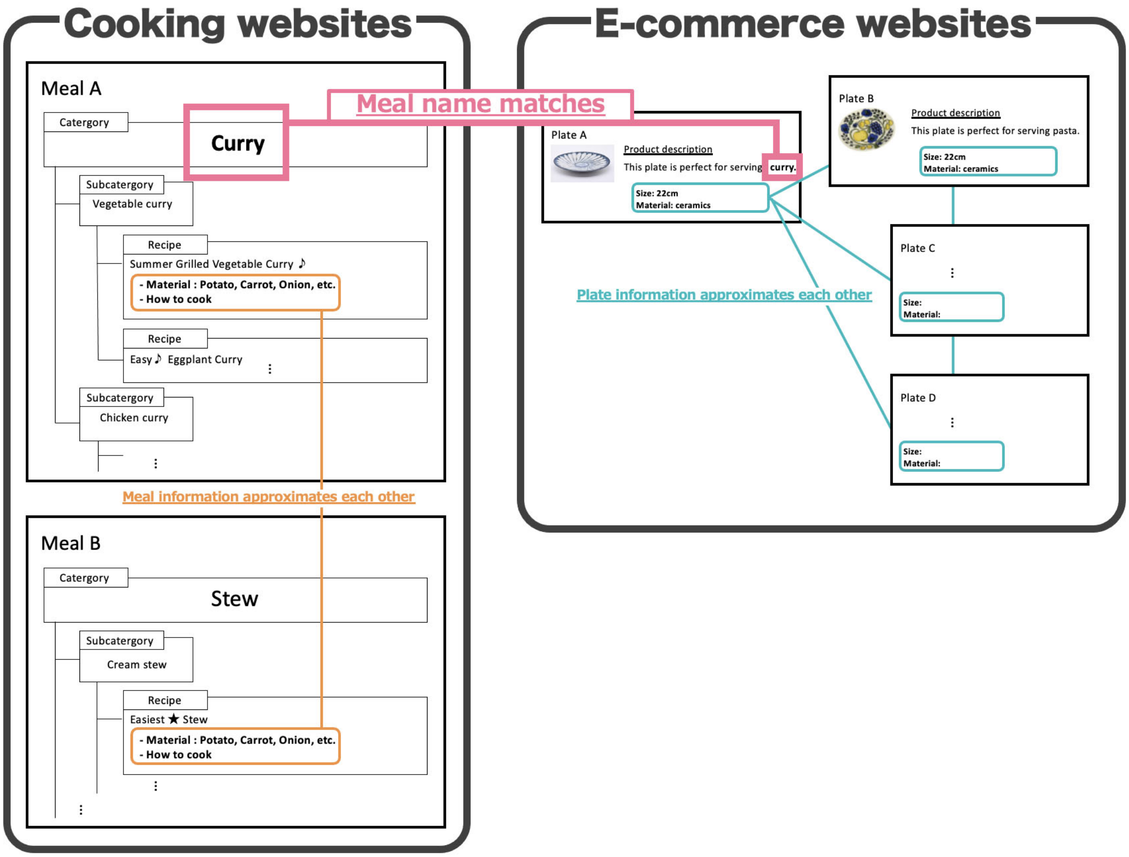

Fig. 5. The connection between meal and plate information on e-commerce websites and cooking websites. E-commerce websites and cooking websites can be connected by a common term, the name of the meal (curry in the case of this figure). Even if the name of the meal is not curry, such as MealB, PlateB, PlateC, and PlateD, it is possible to connect cooking websites and e-commerce websites indirectly by the similarity of the recipe in the case of MealB to that of MealA, or by the similarity of the characteristics of the plates in the case of PlateB, PlateC, and PlateD to those of PlateA. It is possible to connect cooking websites and e-commerce websites indirectly.

large and medium categories, and the names in the small category are considered standard menu items likely to be prepared daily.

These two steps connect meal and plate information via meal names on each e-commerce and cooking website. Figure5 shows the connection between the two. By connecting e-commerce and cooking websites with a typical meal name, meal information on cooking websites and plate information on e-commerce websites are connected. For example, meals prepared using these ingredients and cooking procedures can be served on plates of this size, shape, and material. This is not only a connection between one meal and one plate but also a connection between multiple meals and multiple plates. In the figure, meal A and plate A are connected by the typical meal name, “curry.” Because meals A and B were prepared with similar ingredients and cooking procedures, plate A that can be used for meal A may also be used for meal B. Similarly, plates A and B have the same size, shape, and material; therefore, plate B may also be used for meal A.

5. Extraction of the meal names in the product description

Conditional random field (CRF)[7] is a method of extracting meal names from product descriptions. CRF is a discriminative model that learns the structure of the relationship between a series and labels and infers the classification result that matches the series. By learning the expressions before and after the meal name in the product description with the meal name, a description corresponding to the meal name can be inferred from the product description.

Table 4. Relationships between data employed to obtain the meal names in product description

	The plate category products of Rakuten Ichiba Dataset	Test set	Plates that include the name of Rakuten Recipes' cooking category in the product description	Training set
Number of all documents	1,223,421	-	172,110	-
Number of unique documents	556,975	167,091 (55,697×3times)	134,002	44,667

Table 5. Estimation results by number of updates

	Total number of morphemes as B-DISH	Number of morphemes in Rakuten's meal categories	Number of morphemes not in Rakuten Recipes	Newly meal names	Total number of morphemes in Rakuten Recipes and newly meals
Before update	37,484	36,834	650	156	36,990
First update	37,145	36,855	290	48	36,903
Second update	41,370	41,015	355	28	41,043
Third update	41,958	41,400	558	24	41,424

5.1. Construction of a meal name extraction model

A sklearn-crfsuite was used to implement the CRF. Default values were used for the hyperparameters. Table 4 shows the relationship between the data used for learning and testing. The training and test data were unique descriptions of products belonging to the plate category in the Rakuten Ichiba dataset. The test data comprised 55,697 documents or 10% of the total. During training, we used the descriptions of products belonging to the instrument category of the Rakuten Ichiba dataset as explanatory variables, which included the recipe category names of Rakuten Recipes. The objective variable was the name of the recipe category of Rakuten Recipes. We used 44,667 documents, 1/3 of the training data. Test data and training data overlap. The reason why the product descriptions in the training data may contain meal names that are not included in the recipe category names in Rakuten Recipes.

MeCab[4] was used as the morphological analyzer, and mecab-ipadic-NEologd[1] and recipe category names from Rakuten Recipes were used as the dictionary.

Tagging was performed in the IOB2 tag format, with B-DISH tags assigned to meal names and O tags assigned to names other than meal names. In addition, a preliminary visual inspection revealed that the names of ingredients are likely to occur frequently in the sections where meal names are described; therefore, B-ING tags were assigned to the names of the ingredients. B-ING tags were assigned using "Cooking Ontology" [10]. Three types of morphemes were used to create the features: "three morphemes before and after," "character types of morphemes," and "part-of-speech subdivisions."

Among the morphemes estimated as B-DISH in the constructed model, we extracted those that did not correspond to the names of the recipe categories in the Rakuten Recipes. The extracted morphemes were manually annotated using two items: meal names and other than the meal names. We added morphemes determined to be meal names to the same dictionary and updated the model. The model was updated thrice. This is expected to extract more meal names than the previous process. The amount of data used for a single model update was 55,697 documents for a total of 167,091 documents.

The number of unique series patterns created was 1,303 patterns for the preupdate, 1,314 patterns for the first update, 1,403 patterns for the second update, and 1,407 patterns for the third update.

5.2. Results and discussion of meals name extraction

Table5 lists the estimation results for each update count. Table6 lists the percentage of fits per number of updates and the percentage of meal names (Rakuten recipe category names and newly extracted meals names) among the morphemes estimated as B-DISH. The number of newly extracted meal names decreased with each update, and finally, after three updates of the model, the number of meal names obtained was 117.

The extracted meal names included four types, as follows.

[1] https://github.com/neologd/mecab-ipadic-neologd

Table 6. Percentage of fits per number of updates and percentage of the meal names (Rakuten market meal category names and newly extracted meal names) among morphemes estimated to be B-DISH.

	Fitness rate (number of newly extracted meal names among morphemes that are not meal category names in Rakuten Recipes))	Percentage of meal names (Rakuten's meal category names and newly extracted meal names) among morphemes estimated as B-DISH
Before update	0.24	0.9868
First update	0.17	0.9935
Second update	0.08	0.9920
Third update	0.04	0.9873

- More specific names than Rakuten recipe category names (e.g., Navy curry, White curry, and Pizza)
- More abstract names than Rakuten recipe category names (e.g., Kinpira (Burdock roots cooked in soy sauce and sugar), Simmered, Grilled and Boiled)
- More abstract names than Rakuten notation distortion by Kanji, Hiragana, and Katakana (e.g., Miso soup, sandwich, and Tonjiru (miso soup with pork and vegetables)
- New meal names (e.g., Kuguroff, Croque-monsieur, and Soufflé)

Morphemes that were presumed to be B-DISH but were not meal names include "location information (e.g., hot spring hotel, cafe rice)," "event (e.g., picnic, slumber party)," "drink name (e.g., red wine, cafe au lait)," "brand name (e.g., Dolce and Gabbana, Le Creuset)," and others.

In this study, only three tags (B-DISH, B-ING, and O tags) were assigned; however, it is expected that the estimation accuracy will be improved by creating tag categories from morphemes other than the meal names extracted in this study. In addition to the verification in this study, this tag can also be used as a specialized tag to extract certain unique expressions from product descriptions on e-commerce websites.

6. Conclusion

This study proposed a "meals–plates exploration cycle" to enable users to select a plate that enhances their QoD. We defined "understanding characteristics of each meal and plate and the appropriate combination of both" and "reflection of user's preference" as two elements that should be satisfied to support the selection of a plate to improve QoD. In the "meals–plates exploration cycle," the user uses various plates many times while satisfying these two elements, repeating trial and error to deepen his/her own understanding of the plates to improve their own QoD.

In the future, we will organize the names of meals on e-commerce and cooking websites extracted in Section5 into a hierarchy. Next, we will construct the network described in Section4 by organizing the meal information connected by the hierarchical organization. Finally, we will implement a system that can enable users to explore the constructed network.

Acknowledgment

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References

[1] Cookpad Inc., 2015. Cookpad dataset, the informatics research data repository, the national institute of informatics (dataset), https://doi.org/10.32130/idr.5.1.
[2] Geleijnse, G., Wang, L., Li, Q., 2010. Promoting tasty meals to support healthful eating, in: Wellness Informatics (WI) Workshop at CHI 2010.
[3] Harrar, V., Piqueras-Fiszman, B., Spence, C., 2011. There's more to taste in a coloured bowl, in: Perception, pp. 880–882.
[4] Kudo, T., Yamamoto, K., Matsumoto, Y., 2004. Applying conditional random fields to japanese morphological analysis, in: Proceedings of the 2004 Conference on Empirical Methods in Natural Language Proceeding, pp. 230–237.

[5] Majumder, B.P., Li, S., Ni, J., McAuley, J., 2019. Generating personalized recipes from historical user preferences, in: Proc. 2019 Conf. on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), p. 5976–5982.

[6] Marchionini, G., 2006. Exploratory search: from finding to understanding. Communications of the ACM 49, 41–46.

[7] McCallum, A., 2012. Efficiently inducing features of conditional random fields. arXiv preprint arXiv:1212.2504 .

[8] Michel, C., Woods, A.T., Neuhäuser, M., Landgraf, A., Spence, C., 2015. Rotating plates: Online study demonstrates the importance of orientation in the plating of food. Food Quality and Prefere 44, 194–202.

[9] Mori, S., Maeta, H., Yamakata, Y., , Sasada, T., 2014. Flow graph corpus from recipe texts, in: Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC'14), pp. 2370–2377.

[10] Nanba, H., Doi, Y., Takezawa, T., Sumiya, K., Tsujita, M., 2014. Construction of a cooking ontology from cooking recipes and patents, in: Proceedings of Workshop on Smart Technology for Cooking and Eating Activities(CEA2014), pp. 507–516.

[11] Piqueras-Fiszman, B., Alcaide, J., Roura, E., Spence, C., 2012. Is it the plate or is it the food? assessing the influence of the color (black or white) and shape of the plate on the perception of the food placed on it. Food Quality and Preference 24, 205–208.

[12] Piqueras-Fiszman, B., Harrar, V., Alcaide, J., Spence, C., 2011. Does the weight of the dish influence our perception of food? Food Quality and Preference 22, 753–756.

[13] Rakuten Inc., 2014. Rakuten dataset, the informatics research data repository, the national institute of informatics, https://doi.org/10.32130/idr.2.0.

[14] Wang, L., Li, Q., Li, N., Dong, G., Yang, Y., 2008. Substructure smilarity measurement in chinese recipes, in: Proc. 17th Int. Conf. on World Wide Web, pp. 979–988.

[15] White, R.W., Kules, B., Bederso, B., 2005. Exploratory search interfaces: categorization, clustering and beyond: report on the xsi 2005 workshop at the human-computer interaction laboratory, university of maryland, in: ACM SIGIR Forum, pp. 52–56.

[16] White, R.W., Roth, R.A., 2009. Exploratory Search Beyond the Query-Response Paradigm. Morgan and Claypool Publishers.

[17] Zellner, D.A., Lankford, M., Ambrose, L., Locher, P., 2010. Art on the plate: Effect of balance and color on attractiveness of, willingness to try and liking for food. Food Quality and Preference 21, 575–578.

[18] Zellner, D.A., Loss, C.R., Zearfoss, J., Remolina, S., 2014. It tastes as good as it looks! the effect of food presentation on liking for the flavor of food. Appetite 77, 31–35.

[19] Zhang, Q., Hu, R., Namee, B., Delany, S., 2008. Back to the future: Knowledge light case base cookery, in: Proc. 9th ECCBR, pp. 239—248.