Surprising Recipe Extraction based on Rarity and Generality of Ingredients

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Abstract: Many surprising recipes that utilize different ingredients or cooking processes from normal recipes exist on user-generated recipe sites. The easiest way to find surprising recipes is to use the search function of the recipe sites. However, the titles of surprising recipes do not always include a keyword, such as “surprise”, or an indication that a recipe is unusual in any way. Therefore, we cannot find surprising recipes very easily. In this paper, we propose a method to extract surprising or unique recipes from those user-generated recipe sites. We propose an RF-IIF (Recipe Frequency-Inverse Ingredient Frequency) based on TF-IDF (Term Frequency-Inverse Ingredient Frequency). First, we calculate the surprising value of the ingredients by using RF-IIF. Then, we calculate the surprising value of each recipe by summing the surprising values of the ingredients that appear in a recipe. Finally, we extract recipes that have high surprising values as surprising recipes of the dish category. In the evaluation experiment, the subjects requested an evaluation about each surprising recipe. As a result, we showed that the extracted recipes were valid recipes and also had a surprising or unusual element. Therefore, we showed the usefulness of the proposed method.

1 INTRODUCTION

Planning meals for every day of the week is very hard. Recently, many user-generated recipe sites, where anyone can freely post their recipes, have appeared on the Internet. The number of recipes and users on these user-generated recipe sites are increasing every year. Visitors to the site can use the search function on the recipe sites to find recipes for their desired dishes. Thus, many people use user-generated recipe sites when they are in the planning stage of their dishes and meals.

On user-generated recipe sites, there are not only normal recipes, but also surprising or unusual recipes. A “surprising recipe” has different ingredients or cooking processes from the normal or traditional version of the recipe. When a person feels tired of normal recipes, they are able to cook a wider variety of dishes if they can browse surprising recipes. The easiest way to find surprising recipes is to use the search function of the recipe sites. However, the titles of surprising recipes do not always include the keyword “surprise”. Therefore, we cannot find those unique recipes simply by using the search function. Many surprising recipes are buried within the long lists of “normal” recipes.

We propose using RF-IIF (Recipe Frequency-Inverse Ingredient Frequency) based on TF-IDF to calculate the “surprise” value of an ingredient in a recipe. The surprise value of a recipe is calculated by summing the surprising values of ingredients used in the recipe.

The next section describes application scenarios, while Sections 3, 4, and 5 discuss our proposed method in detail and evaluate it. In Section 6 we introduce related work and Section 7 discusses future work and concludes the paper.

2 APPLICATION SCENARIOS

Suppose that a housewife who cooks every day from her normal repertoire wants to make a different version of a dish from her standard fare. In that situation, we consider that her satisfaction level will increase if she can browse surprising, new recipes on user-generated recipe sites.

For example, suppose that she wants to eat ground steak, but is tired of standard ground steak recipes. However, she can find a surprising recipe for ground steak, which uses cucumber sauce, for example, if she uses our proposed method. As another example,

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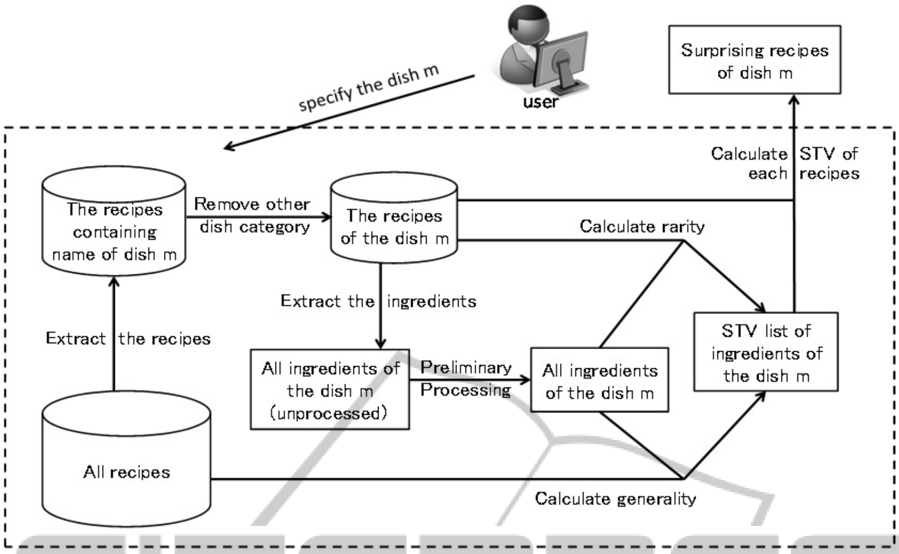


Figure 1: Overview of our proposed method.

let's assume that she wants to find a surprising recipe for pasta. In this case, she can find recipes, such as one for cream pasta, which uses rice powder. Yet again, she is able to create a surprising recipe if she uses our proposed method, rather than a traditional cookbook.

In our proposed method, the user can specify the name of his or her favorite dish. Therefore, she can browse a few different recipes than those she usually makes. Thus, our proposed method is effective when she wants to eat a slightly different dish, even if she doesn't want to try a completely new recipe.

3 APPROACH

In this paper, we calculate each surprising value of an ingredient of the dish category specified by a user to extract surprising recipes. We define surprising recipes as those that use surprising ingredients. Additionally, we define surprising ingredients as ones that have a low frequency of appearance in certain dish recipes within the specified category, but have a high frequency of appearance in other dish recipes.

First, we extract recipes from the dish category (e.g., ground steak) that are specified by a user from all recipes on the user-generated recipe site. Some of the recipes in the user-generated recipe site are categorized, but many of them are not categorized.

Therefore, we extract all recipes containing the name of the dish category specified by a user in the recipe name. However, recipes of other categories may exist in the extracted recipes. Therefore, we remove recipes from other categories from this set of recipes and extract all the ingredients in these recipes by the methods described in 3.1 and 3.2. Then, we calculate surprising values of the ingredients described in 3.3, and finally, we extract surprising recipes by using the surprising value of ingredients described in 3.4. We show an overview of our proposed method in Figure 1.

3.1 Remove other Category Dishes

For example, we extract recipes containing "ground steak" in the recipe title when we want to extract ground steak recipes from the list of all recipes. However, some extracted recipes may not belong to the specified category. For example, the recipe whose title is "ground steak bread" which should belong to the "bread" category, can be extracted when the user specify the category "ground steak". Therefore, we remove these recipes with the following method. First, we make lists of categories of dishes on the user-generated recipe site. However, we can remove the category from the lists if the dish name that we want to extract contains the category name. For example, we want to extract recipes of "ground steak", but there is also "steak" on the list. Then, we remove recipes from the extracted recipes if the recipe title contains words on that list. As a result, we will extract only the ground steak recipes.

3.2 Preliminary Processing

On a user-generated recipe site, users can write down ingredients and the cooking processes of specific recipes. Thus, the descriptions have words that are not ingredients (e.g., comments for readers), including spelling variations and extra words (e.g., "*", "(1)", "(2)"). First, we limit our search to only ingredient names by removing symbols such as "*" and "(1), (2), …", as well as parentheses like "(bigger)". Then, we remove spelling variations of ingredients. In this paper, we manually compile a list of spelling variants of ingredients within two categories of dishes in our evaluation (see section 4)[1]. We consider we can automate this process using such techniques (Young, 2012), (Maarten, 2008) on spelling variations. We plan to apply these techniques in the future. Finally, we manually remove words that are clearly not ingredients.

3.3 Calculating Surprising Theoretical Value of Ingredients

Let *m* represent the dish category specified by a user. Ingredients with a low frequency of appearance in the dish category m have possibility for surprising ingredients within the dish category m. However, such ingredients may not be well known among users. If the user does not know the ingredients at all, she might not feel that they are surprising. In this paper, we propose that users feel surprised when they are recommended to use ingredients that are well known, but do not normally come up as ingredients for the specified dish category. [i]Moreover, if the ingredients are very rare, users cannot buy them in normal supermarkets. Therefore, among those ingredients that have a low frequency of appearance in the specified dish category, the ingredients with a high frequency of appearance in *all* recipes are considered surprising recipes within the dish category m.

The technique, called TF-IDF (Term Frequency-Inverse Document Frequency) is used to obtain the characteristic word in a certain document. TF is the frequency of appearance of words in the document. IDF is the inverse frequency of appearance of words in the document set. TF-IDF, which represents the weight of a certain word, is calculated by multiplying the TF and the IDF. In other words, the weight of the word that appears frequently in a certain document but does not appear in other documents is high. Thus, it is possible to obtain the characteristic words of a certain document. Many people utilize a method based on TF-IDF in fields that involve information retrieval (Jiaul, 2013), (Luis, 2012), (Senthil, 2012).

In this paper, we define surprising ingredients of a certain dish category as "the ingredient that have a low frequency of appearance in the specified category, but a high frequency of appearance in other categories". This is similar to the idea of TF-IDF. In order to extract surprising ingredients, we propose RF-IIF (Recipe Frequency-Inverse Ingredient Frequency), which is based on TF-IDF, to calculate the surprising value of each ingredient. We call the resultant value that is calculated based on RF-IIF as the *surprising theoretical value (STV)*.

$\text{RF-IIF}_{i,m;p}$ (Equation (1)) represents the surprising value of ingredient i among the dish category m, specified by a user, with the parameter p. $\text{RF-IIF}_{i,m;p}$ is calculated from RF_i (Equation (2)) and $IIF_{i,m}$. RF_i represents the generality of the ingredient i, and $IIF_{i,m}$ (Equation (3)) represents the rarity of the ingredient i within the dish category m. R_{all} is the number of all recipes, R_i is the number of recipes including the ingredient i within the list of all recipes, R_m is the number of recipes in the dish category m, $R_{i,m}$ is the number of recipes that include the ingredient i within the dish category m. The parameter p is used for adjusting the weight of the rarity and generality of ingredients. We can extract ingredients with higher rarity from the dish category m by increasing p.

$$RF\text{-}IIF_{i,m;p} = RF_i \times IIF_{i,m}^{p} \tag{1}$$

$$RF_i = \frac{R_i}{R_{all}} \tag{2}$$

$$IIF_{i,m} = \log \frac{R_m}{R_{i,m}} \tag{3}$$

3.4 Calculating Surprising Theoretical Value of Recipes

On most user-generated recipes sites, recipes usually consist of five elements: title, completion image, ingredients list, cooking process, and a comment by the poster of the recipe. We think that most posters will emphasize the inclusion of an ingredient when they use it as a surprising ingredient. In this case, they are likely to write the ingredient name on the comment column. We morphologically analyze the comments connected to the recipes of the dish category m. If an ingredient name occurs in the comment section of the recipe, then we add its surprising value to the STV of the recipe. In this way, we can calculate the STV of recipes.

[1] We also applied the list to the third category. As a result, we were able to remove the spelling variants of ingredients without problem.

Specifically, we define E as a set of elements that are used to calculate STV of the recipe and we define I_e as a multi-set of ingredients within element E. We define $S_{r,m;p}$ as the STV of recipe r in dish category m when the weight parameter is p. $S_{r,m;p}$ is calculated by

$$S_{r,m;p} = \sum_{e \in E} \sum_{i \in I_e} RF\text{ - }IIF_{i,m;p} \tag{4}$$

4 EVALUATIONS

4.1 Abstract of Evaluations

We evaluated the surprising recipes that were recommended by our proposed method. Our results demonstrate the effectiveness of our proposed method.

We extracted surprising recipes from the dish categories of “ground steak”, “pasta” and “gratin” from a user-generated recipe site with our proposed method. The weight parameter p was set to 5 because we had obtained a good result beforehand. Then, we extracted 10 recipes with the top 10 STVs as surprising recipes from each dish category.

In order to evaluate the validity of the extracted surprising recipes, we conducted a questionnaire survey. We presented the full text of the surprising recipe in the questionnaire. The subjects were asked to evaluate the text using a five-point Likert scale in terms of the *surprising value* and *proper value* of each surprising recipe. The surprising value represents whether or not the recipe is surprising or unusual from the subject’s perspective. The proper value represents whether or not the recipe tastes delicious to the subject. Furthermore, we asked the subjects about their sex, age, and the usefulness of the proposed method using a five-point Likert scale. Table 1 represents the details of the questionnaire regarding surprising value, proper value, and the usefulness of the proposed method.

We divided the subject into two groups; one is a group of specialists and the other is a group of non-specialists. Specialists are those who have the qualification of a chef or a dietitian. Non-specialists could include anyone else. We collected the answers of three specialists and 10 non-specialists about the ground steak, answers from three specialists and 13 non-specialists about the pasta, and responses from five specialists and 15 non-specialists regarding the gratin. The sex ratio of male to female was 6:4 and 90 percent of the subjects were in their twenties.

Table 1: Details of the questionnaire about surprising value, proper value, and the usefulness of the proposed method.

	surprising value	proper value	usefulness of the proposed method
5	very surprised	seems very delicious	very useful
4	surprised	seems delicious	useful
3	neutral	neutral	neutral
2	unsurprised	seems unappetizing	unuseful
1	very unsurprised	seems very unappetizing	very unuseful

4.2 Dataset

It is possible to extract surprising recipes using our proposed method from Food.com, Allrecipes.com and other similar sites, but in this paper, we used data from COOKPAD (COOKPAD), which has the highest number of Japanese users and recipes in terms of user-generated recipe sites. We collected data from 1,492,366 recipes and 12,826,094 ingredients from COOKPAD. We conducted experiments on recipes for ground steak, pasta, and gratin because in most recipes for ground steak and gratin, relatively standard ingredients are typically used, whereas in recipes for pasta, a wide range of variation in seasoning and ingredients exists. All of the researched dishes are very popular in Japan.

We extracted 12,327 recipes and 161,307 ingredients which contained the keyword “ground steak” in a recipe title, 37,426 recipes and 371,797 ingredients that contained the keyword “pasta” in a recipe title, and 14,056 recipes and 140,782 ingredients that contained the keyword “gratin” in a recipe title. Next, we removed recipes that belonged to other categories using the technique described in 3.1. After that, we extracted 11,645 recipes and 156,852 ingredients for ground steak, 35,593 recipes and 367,837 ingredients about pasta, and 12,240 recipes and 122,995 ingredients related to gratin. Then, we removed spelling variants and extra words of ingredients using the technique described in 3.2.

4.3 Results

Table 3 represents the top 20 ingredients ranked by surprising values that were obtained through our proposed method. Cucumber and sweet potato are found in the ground steak list, banana and konnyaku for the pasta, and chocolate or kelp for the gratin. These ingredients, which have high STVs, are not thought to be traditionally used for making those dishes. Table 4 represents the extracted surprising

Table 3: Example about STV of ingredients.

	ground steak		pasta		gratin	
rank	ingredient name	STV	ingredient name	STV	ingredient name	STV
1	bread flour	516	baking powder	1662	dry yeast	1711
2	baking powder	410	pancake mix	1406	cocoa	989
3	cucumber	247	vanilla	1144	baking powder	955
4	chicken leg	235	dry yeast	770	pancake mix	756
5	salt-free butter	212	banana	768	vinegar	603
6	fried tofu	209	cocoa	674	gelatin	583
7	fat-free milk	190	rice	437	cucumber	528
8	pasta	189	strawberry	336	chili oil	520
9	ham	169	chocolate	298	powdered gelatin	486
10	rice	143	coating of egg roll	293	kelp	484
11	fried oil	138	rice flour	253	sesame	369
12	sweet potapo	132	brown sugar lump	239	chocolate	355
13	apple	115	egg white	214	ginger	331
14	sausage	114	tempura flour	207	bean vermicelli	294
15	dried bonito	110	konnyaku	194	chocolate bar	293
16	cake flour	108	bread	191	chinese chive	285
17	chili bean sauce	108	scinnamon	191	pickled plum	268
18	plain yogurt	103	shortening	182	lettuce	267
19	seasoned cod roe	101	green powder	167	bread flour	257
20	cream cheese	99	dough	158	whole wheat flour	242

recipes calculated by the STV of their ingredients. We analyzed the results of the questionnaire. Table 5 represents the *average of surprising measure value (ASMV)* and *average of proper measure value (APMV)* about each dish. SMV of the recipe represents the percentage of the persons who selected "very surprised" or "surprised" from a five-point Likert scale about the recipe. ASMV is average of SMV of all recommended recipes (10 recipes). The same may be said of APMV.

ASMVs of non-specialists are higher than ASMVs of specialists. That is because specialists have more knowledge of the ingredients and dishes than non-specialists and specialists are aware of various cooking methods that use non-traditional or surprising ingredients. Moreover, we can say that the extracted recipes are useful because APMVs are 50 percent or more, and the maximum of APMV is nearly 80 percent.

Figure 2 represents graphs of ASMVs of top x recipes ranked by STVs. For example, Figure 2 represents ASMV of the top 5 recipes ranked by STVs when x=5. From Figure 2, we know that SMV tends to decrease with a decreasing STV. The graph about the gratin is slightly different from the others, but it shows the same result when x=4 or more. Therefore, we can say that STV roughly correlates with the SMV of the actual recipe.

Table 6 represents the percentage of the people who selected "very useful" or "useful" for the usefulness of the recommended recipes. More than 60 percent of subjects think that the recommended recipes are useful, except for ground steak. Thus, we can say that there would be a demand for our proposed method of finding and extracting surprising recipes from user-generated recipe sites.

5 DISCUSSION

First, we will discuss Table 5. Because specialists have more knowledge of the various ingredients and dishes than a non-specialist, we assumed that the specialists would consider many recipes "not surprising". Thus, we suggest that we can extract recipes that are well known for specialists but are relatively unknown to non-specialists. Moreover, we know from Table 5 that the evaluation results of pasta are the lowest of the three. There are standard ingredients for gratin, and recipes of gratin are almost all similar to each other. The same is true for ground steak. In contrast, there are various recipes for pasta because there are many kinds of pasta sauces and various uses of pasta itself. For this reason, there is the possibility that many people would not feel surprised at certain recipes, even if she is recommended a recipe that she had never seen before. Therefore, we think that the evaluation

Table 4: Titles of extracted surprising recipes.

rank	ground steak	pasta	gratin
1	Good in summer. Ground steak of yam and cucumber	Simple. Tropical curry soup pasta	Ginger cream gratin of vegetables
2	Good in summer! Grated cucumber ground steak	Pasta sauce. Rice gratin	Vinegar potato gratin
3	A bite-size tofu ground steak. Chock taste	Simple. Pasta dipped in rice flour gratin of soft-boiled egg	Salt kelp yogurt! Healthy gratin of fish
4	My favorite. Natto ground steak	Isoflavone. Rice pasta	One material. Gratin of salt kelp and radish
5	Magic powder!? Ground steak plump anyone	Simple cream pasta with rice flour	Egg gratin of spinach and kelp
6	Ground steak refreshing in vegetables	To diet! Increased bulk pasta ultimate	Refreshing healthy gratin of chinese cabbage and penne
7	Simple shotening of time lunch. Cheese ground steak rice	Japanese-style rice flour pasta of seasoned cod roe and maitake mashroom	Side dish gratin of avocado and salt kelp
8	Ground steak. Japanese-style apple sauce	Creamy tomato pasta	Gratin of avocado and soybean curd
9	Soy pulp ground steak	Rice flour. Cream pasta of bok choy and bacon	Texture of seaweed is a decisive factor. Excellent gratin
10	Soybean plenty ground steak	Scallop. Young sardines. Garlic pasta	Super easy! Potato gratin to make with HM

Table 5: The result of the questionnaire about the ASMV and APMV.

	ground steak		pasta		gratin	
	ASMV	APMV	ASMV	APMV	ASMV	APMV
non-specialist	0.62	0.62	0.55	0.78	0.81	0.75
specialist	0.23	0.67	0.17	0.57	0.60	0.74

Table 6: The results of the questionnaire about the usefulness of the proposed method.

	ground steak	pasta	gratin
non-specialist	0.70	0.85	0.87
specialist	0.33	0.67	0.80

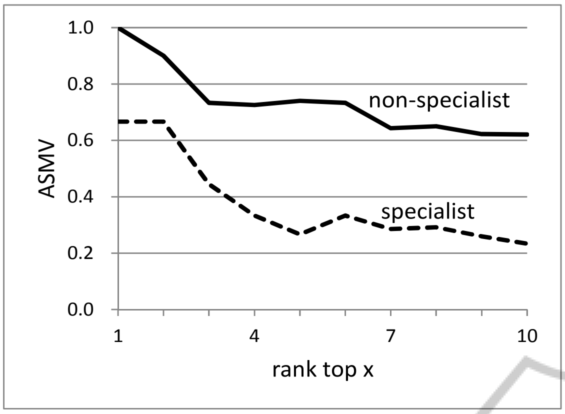
resultof pasta is the lowest of the three. We suggest that our proposed method is more effective to use for dish categories that are commonly composed of standard recipes.

In addition, as represented in Table 6, more than 60 percent of the subjects selected “very useful” or “useful” for the recommended recipes, and more than half of subjects answered that the proposed method is useful. The ratio of answering “very useful” or “useful” about recommended recipes of ground steak is the lowest of the three, although the ASMV of ground steak is higher than that of pasta. This represents that usefulness is not dependent on the ASMV of a recipe. As mentioned above, we think that there are many restaurants that prepare unusual ground steak, but there are fewer restaurants that offer unusual pasta and gratin. Thus, we think that the impression of a recipe being surprising for ground steak is less than potentially surprising recipes for pasta and gratin. We consider that if surprising recipes of pasta and gratin exist, many people would want to know them. For this reason, we think that the usefulness of ground steak is the lowest of the three.

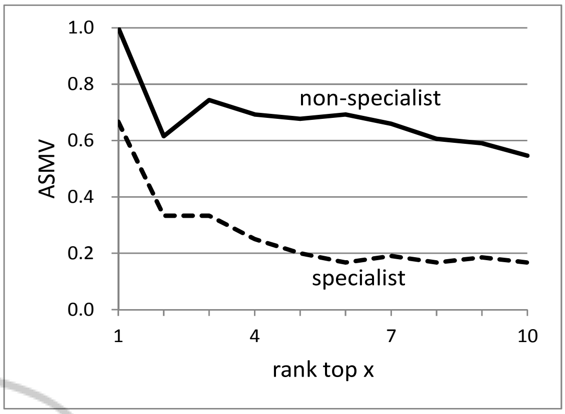
Our proposed method extracts surprising recipes by specifying the name of the dish category. Therefore, we cannot use our proposed method directly in a situation where an individual wants to know a recipe that uses all the ingredients in the refrigerator. Therefore, we think that the usefulness may improve even further by proposing a method that can extract a surprising recipe by specifying names of ingredients, rather than by the name of the dish category.

6 RELATED WORK

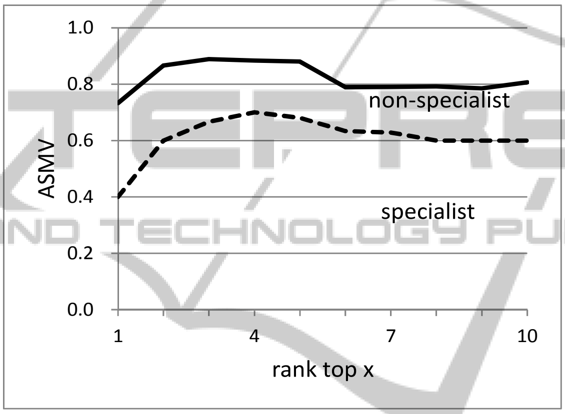
A great deal of research about the recipe of the dish exists. The user has the taste of various ingredients, so the user may not be satisfied if they are recommended the same recipe. Then, a recipe recommendation system that considers the taste of



(a) Ground steak



(b) Pasta



(c) Gratin

Figure 2: ASMVs of top x recipes ranked by STVs.

an individual exists. Ueda et al. (Ueda, 2008) calculated the score of each ingredient by using the technique based on TF-IDF from the cooking history of a user. They then calculated the score of the recipe from the score of its ingredients. The high score recipe was recommended as a suitable recipe for a specific user. Moreover, Ueda et al. (Ueda, 2011) estimated the score of likes and dislikes about various ingredients from the browsing history and cooking history of a user. Then, they calculated the score of the recipe from the score of its ingredients. Furthermore, they set up a variable of time, so recommendations for cooking similar recipes would not happen every day. Moreover, Maruyama et al. (Maruyama, 2012) recognized ingredients, through image processing techniques, in images that site users were taking on their mobile devices. The system could then recommend a suitable recipe that used the recognized ingredients.

These recipe recommendation systems that are being considered do exist. Yajima et al. (Yajima, 2009) calculated the cooking difficulty of a recipe from its ingredients, as well as the cooking processes involved in the recipe by inputting ingredients, seasoning, and personal taste of a user. Additionally, a suitable recipe for the situation could be recommended by inputting the schedule of a user. Moreover, Akazawa et al. (Akazawa, 2012) recommended recipes that could utilize the ingredients in the refrigerator of a user by inputting the quantity of the ingredients and their “best before” date that were found in the user’s refrigerator. They also calculated the leftover quantity of the ingredients that were purchased, which would remain after the necessary amounts of ingredients were used for the recipe. In this way, the user does not need to input all of the information the next time.

A recommendation system that offers dietary therapy support also exists (Kitamura, 2009)(Tagawa, 2013)(Youri, 2011)(Jill, 2010). Tagawa et al. calculated the nutritional values of recipes by making Linked Data from information about the recipe and the Japanese standard ingredient composition table. They obtained the results of the nutrition calculation of the recipe by comparing the name of the recipe to the same dish name on the menu of the restaurant, then estimating the nutritional facts about the menu of the restaurant. In addition, the system distinguishes whether or not a menu is a suitable menu in terms of nutritional content by registering age, weight, and amount of exercise of a user into the system. Moreover, Youri et al. proposed the recommendation system for healthy recipes. The system discriminates important feature of the original recipe from its text, and creates the feature vector, then calculates the similarities between recipes. If the similar recipe has a high health index, then the original recipe is replaced by it.

Research about alternative ingredients in recipes also exists. Karasawa et al. (Karasawa, 2004) calculated the feature score of ingredients and the cooking action of each recipe group by classifying the recipes and using TF-IDF. They regarded the ingredients that had a low feature score as general ingredients. The system extracts the ingredients that are normal and have a frequency of appearance in a recipe group as ingredients that could substitute. Moreover, Shidochi et al. (Shidochi, 2009) proposed a system that extracts the ingredients and the cooking action from each recipe text, and they obtained the characteristic cooking action of each ingredient by using TF-IDF. Furthermore, the system creates the vector of the cooking action of the ingredients, along with the characteristic cooking action of the ingredients in the same dish category. Then, the system extracts the ingredients that have the vector of the cooking action with high cosine similarity as the ingredients that can be substituted. Moreover, Chun et al. (Chun, 2012) built a network of ingredient complements and a network of ingredient substitutes. They extract alternative ingredients and remove ingredients used as options by using both of their networks.

Fang et al. (Fang, 2012) proposed a system that generates a menu (set of multiple recipes) for dinner, as an example. The system calculates the similarity between recipes from their ingredients. Moreover, they obtained the co-occurrence relation of the recipes from the site so a menu can be recommended. Finally, the system generates a menu that consists of a group of suitable recipes by inputting the ingredients obtained by a user

In the field of information recommendation in recent years, a system that recommends information suited to the taste of the user has come under some criticism, mainly because it has been argued that it may not actually improve the satisfaction level of the users. Instead, the element of surprise and novelty about the information has attracted more attention. (Murakami, 2008)(Yuan, 2012). However, these systems recommend the information which is of little interest to the user and never browsed by using the user information. Therefore, it cannot be used for our proposed method because their purpose is different from our purpose.

As this section has made very clear, many research studies about cooking recipes and recommending culinary information exist. However, there have not been any studies that focused on the element of surprise about a recipe and its ingredient, so the purpose and the techniques of the past studies are different from our proposed method.

7 CONCLUSIONS AND FUTURE WORK

In this paper, we proposed a method that extracts surprising recipes from a dish category specified by a user on user-generated recipe sites by using the frequency of appearance of surprising ingredients.

We calculated the STV of each ingredient based on RF-IIF, which is calculated from the rarity score and the generality score of the ingredient. The rarity score is the frequency of appearance of the ingredient in the dish category, while the generality score is the frequency of appearance of the ingredient in all of the site's recipes. Then, we calculated the STV of each recipe based on the STV of its ingredients, and extracted 10 surprising recipes that had the top 10 highest STVs in three dish categories ground steak, pasta, and gratin. In the evaluation experiment, the subjects were requested to make an evaluation about the surprising value and the proper value of each surprising recipe. As a result, we showed that 80 percent of the subjects answered "seems very delicious" or "seems delicious" about the extracted recipes, and more than half considered the recipes to be surprising. Moreover, we showed that our proposed method was a valid method by showing that the STV, which is a theoretical value of surprise, has a correlation with SMV, which is the surprise value obtained from the results of the questionnaires.

In any future work, we will improve the accuracy of the surprising recipe extraction. In addition, we will eliminate the redundancy of extracted recipes by first calculating the similarity between recipes. Furthermore, we will consider improvements to the system that can extract surprising recipes by specifying the ingredient names instead of specifying a dish category name.

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