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Constructing Cookery Network based on Ingredient Entropy Measure

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Abstract

Food recipes, from traditional recipes to fusion recipes, are easily uploaded and shared online. Recipes consist of a set of ingredients, the cooking procedure, cooking time, etc. It is not easy to classify recipes in terms of the taste of cooked foods, the cuisine styles, or the characteristics of foods. In this paper, we construct the recipe similarity network by adding edges if two different recipes share common ingredients. For this, we newly define the similarity measure among recipes using the probabilistic entropy measures over ingredients. And we construct the ingredient relation network that shows the correlations of ingredients in the recipes. We show these networks can be applied to show the hierarchical structure of 683 recipes and 375 ingredients and the similar recipes are well clustered according to the entropy measure.

Keywords: Complex Network, Ingredient, Ingredient Entropy, Recipe Entropy, Recipe, Recipe Similarity

1. Introduction

As interest in cooking, the recipes of several cuisines are opened and shared online. The recipes vary from traditional food of many countries to fusion food combined elements of different culinary traditions. In many recipes, how can we classify similar recipes? For example, Korean foods, 'steamed chicken' and 'streamed short-ribs', are different in the main ingredient, but these are included in the same food types. Because the cuisine style and the taste is similar. On the other hand, 'pork ribs' and 'pork ball' are same in the main ingredient, but these are recognized as different food types. Can we distinguish what recipe is easy or difficult to cook and what recipe is for Korean food that we don't know or haven't experienced?

The taste of cooked foods is highly depends on the personal experience or cultural backgrounds. It is not easy to cluster the recipes of various foods of many countries and particularly fusion recipes are hard to cluster similar to any food. It is a so subjective matter to consider the recipe similarity to categorize a set of foods. In this paper, we focus the structure of foods in terms of the correlation of recipes and ingredients. And we analyze the correlation of recipes based on the social network paradigm.

Complex network analysis is a research method to find the structure and the principle in a large number of components and their complex relationship networks. Also the current big data-based network available reveals a new insightful concept and challenging problems in various fields[1,2]. Ahnert[3] proposed a frmaework for the compressed networks of ingredients into power graphs. He presented a way to identify dominant relationship patterns in large-scale networks as well as a general way of defining overlapping node communities for valuable insights.

Some works focused on how to recommend ingredients for the good food and how to replace cooking material by considering the similarity of recipe texts[4–6]. The goal of recipe recommendation was usually to

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suggest recipes to user's food preferences based on their past recipe ratings or history[7,8]. Shidochi et al.[9] proposed a method to find replaceable materials from recipes for the user's requirements. He considered the characteristic cooking actions from a large amount of cooking recipe text, such as calorie constraints and food availability. Geleijnse, et al.[10] designed a prototype of a personalized recipe advice system for users. It assists the users to make health-aware meal choices based on past selections and nutrition intake. Freyne and Berkovsky[11] presented a preliminary study into the suitability of varying recommender algorithms for the recommendation of recipes based data capture and food-recipe relationships.

Recently the social structure among cooking recipes are studied. Kuo, et al.[12] proposed a graph-based algorithm for intelligent menu planning mechanism that constructs a recipe graph to capture the co-occurrence relationships between recipes from the collection of menus. Teng, et al.[13] presented two types of networks, the complement network and the substitute network, to capture the relationships between ingredients. The complement network captures which ingredients tend to co-occur frequently. And it is composed of two large communities, savory and sweet, using ingredient co-occurrence. The substitute network, derived from a user-generated suggestion for modifications, can be decomposed into many communities of functionally equivalent ingredients, and captures users' preference for healthier variants of a recipe. Wang, et al.[14] presented the model of recipe graphs based on workflow-like cooking procedure. They proposed a novel similarity measurement based on the frequent patterns, and devised a filtering algorithm to prune unrelated data so as to support efficient online searching.

In this paper, we have collected 683 recipes from a famous recipe sharing website, Allrecipes.com, and extracted 375 ingredients by regular matching in recipes. And we newly define the similarity between recipes by the entropy measure. Just because two recipes share many common ingredients does not always mean they are similar to each other. To know how similar global recipes are we construct two types of networks, the recipe similarity network and the ingredient relation network based on entropy measure.

The rest of the paper is organized as follows. Section 2 describes the data set and data preparation. In Section 3, we represent our entropy method to measure the similarity of recipes and construct the two types of network. A conclusion is made in Section 4, along with some suggested directions for future work.

2. Data Set Preparation

The web services provide to share easily various recipes of several cuisines and 'Allrecipes.com' is the popular cooking community and the large recipe sharing website that 1 billion people use it every year. It services 18 international sites made by 12 native languages for users and provides the various information about cooking to assist people cooking at home. A recipe contains the information on how to prepare a dish: the list of ingredients, an amount of ingredients, and the type of ingredients, cooking time, cooking procedure and so on.

We collected 683 recipes from all recipes.kr for analyzing recipe network. 465 of them are Korean recipes and 218 of them are foreign recipes. Foreign recipes include 72 Japanese recipes, 49 Chinese recipes, 80 Italian, and 17 Thailand recipes. A recipe that includes the list of ingredients, cooking time, and cooking method is saved as a text file. The preprocessing steps to extract the ingredient names in a recipe are shown in Figure 1.

For analyzing recipes, we first extract all ingredients from recipe files. Ingredients are separated by a line and each line contains an ingredient name, the amount of an ingredient, and the state of an ingredient, such as 'mashed', 'fresh', 'rib', etc. To extract only ingredient names, non-ingredient terms are removed by expression matching. We removed the words of quantifier such as '20ml', '1 cup', 'handful', 'little', or 'half', additional words of ingredient status such as 'chopped', 'thick', or 'fresh' and words of symbol such as '+', '=', etc. Finally, the number of extracted ingredient names is 959. We also simplified the lots of name variations into a single prototype. We classified ingredients into 375 prototypes based on similarity. For example, 'scallion', 'small green onion', and 'spring onion' are classified in the prototype, 'allium'. Table 1 shows the collected number of recipes and ingredients and the simplified number of ingredients.

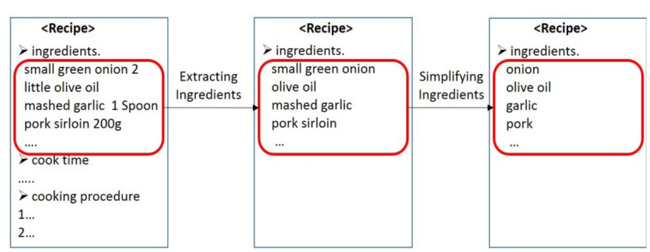


Figure 1. Preprocessing steps to extract the ingredient names.

By calculating the number of ingredients in a recipe, there was no significant difference between a Korean recipe and a foreign recipe. The average number of ingredients used a recipe is around ten for Korean foods and eleven for foreign foods. We show the frequency distribution for both the number of recipes and ingredients in Figure 2 (a) and 2 (b) respectively.

Table 2 shows the frequency rates of ingredients in order in which they appear in most recipes. The most used ingredient in Korean recipes and foreign recipes is 'garlic' that appears for more than 50% of foods. This means 'garlic' is the ingredient that it is for basic flavor rather than for special. The ingredients such as 'garlic', 'salt', 'soy source', 'sugar', 'pepper' and 'onion' are used frequently in both Korean foods and foreign foods.

3. Social Network of Cookery

3.1 Ingredient and Recipe Entropy

For the recipe similarity, we used the method of entropy measure by the probability. Entropy is a quantitative measure of uncertainty and it is the expected value of information content[15–17]. If two ingredients, 'garlic' and 'basil', are used in a recipe, the effects of two ingredients to food will be different. Because 'garlic' is used almost in foods, but 'basil' is rarely used in foods. It means that basil can be an ingredient that special flavors more than 'garlic' and the cooking can be 'difficulty' or 'complexity' if

Table 1. The number of recipes and ingredients

Cuisine	# of recipes	# of ingredients	# of total ingredients	# of ingredient prototypes
Korean	465	676	959	375
Foreign	218	511		

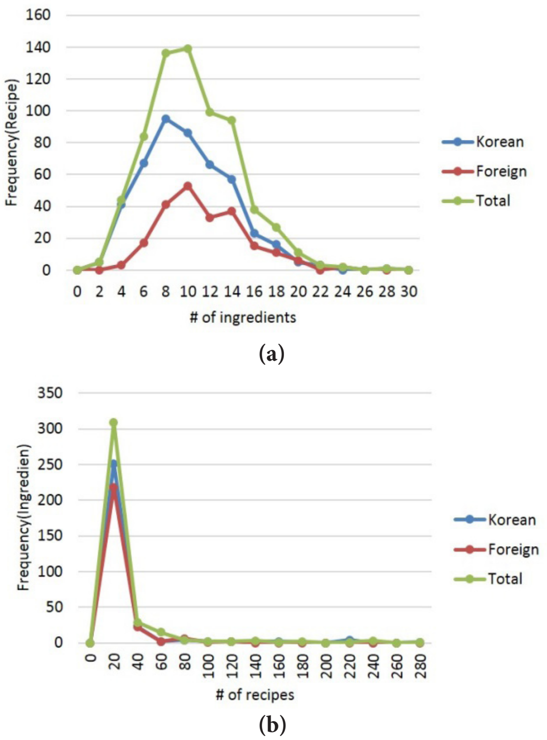


Figure 2. **(a)** Frequency of recipes (y-axis) and the number of ingredients (x-axis). **(b)** Frequency of ingredients (y-axis) and the number of recipes (x-axis).

Table 2. Ranking and frequency rates of ingredients

Ranking	Korean recipes		Foreign recipes		Total recipes	
	Ingredient	Frequency	Ingredient	Frequency	Ingredient	Frequency
1	Garlic	58%	Garlic	50%	Garlic	56%
2	Welsh onion	46%	Salt	47%	Salt	46%
3	Salt	45%	Pepper	41%	Soy source	41%
4	Soy source	45%	Onion	35%	Welsh onion	40%
5	Sesame oil	43%	Soy source	33%	Sesame oil	35%
6	Sesame	35%	Sugar	33%	Pepper	34%
7	Sugar	33%	Cooking oil	32%	Sugar	33%
8	Onion	31%	Olive oil	30%	Onion	32%
9	Pepper	30%	Welsh onion	28%	Sesame	26%
10	Powdered red pepper	26%	Egg	25%	Cooking oil	24%

basil is included in a recipe. We measured the ingredient entropy and the recipe entropy using the frequency probability of ingredient and described the calculating process from Equation 1 to Equation 6.

In this paper, we denote R, the set of all recipes we collected such as

$$R = \{r_1, r_2, \cdots, r_m\} \quad (1)$$

So r_i denotes the specific recipe we prepared. And from R, we make another set, I, the set of all ingredients (cooking materials).

$$I = \{i_1, i_2, \cdots, i_n\} \quad (2)$$

Thus, i_p are contained in a member of R at least once in a recipe. Each recipe consists of a set of ingredients such as

$$r_x = \left\{i_{x_1}, i_{x_2}, \cdots, i_{x_k}\right\} \quad (3)$$

So $|r_x| = k$ means that the recipe r_x consists of k different ingredients. We assume that $|I| = n$ and $|R| = m$ in the following. First we define $P(i_x) = P_x$, the probability of the ingredient i_x which is the random chance that an ingredient is a member of a recipe r_r randomly chosen.

$$P(i_x) \equiv P_x = |\{r_i \,|\, i_x \in r_i\}| / (m = |R|) \quad (4)$$

Using this, we can define $E(i_x)$, the entropy for ingredient i_x as follows.

$$E(i_x) = -\log P(i_x) \quad (5)$$

So we know that the rarer the ingredient is, the higher $E(i_x)$ is. And by summing up all entropies of ingredients contained in a recipe, we also define $E(r_x)$, the entropy of r_x as follows.

$$E(r_x) = \sum_{i_k \in r_x} E(i_k) \quad (6)$$

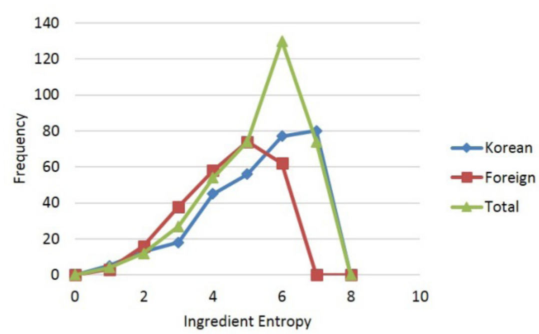
We insist that this newly defined recipe entropy would be one measure of the cooking 'difficulty' and one measure of the food preparing complexity since the more ingredients and the rarer ingredient will increase the workload for a cooking procedure.

We show the frequency distribution of the ingredient entropies and the recipe entropies in Figure 3(a) and 3(b). It shows a similar pattern with the distributions of Korean and foreign. The entropy of Korean ingredients is little higher than that of foreign, but the entropy of Korean recipes is little lower than that of foreign.

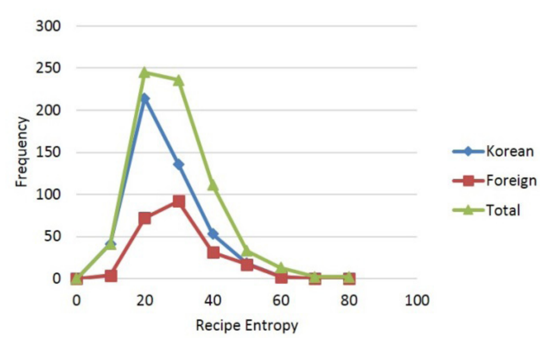
Table 3 shows the entropy and the entropy ranking of Korean recipes and foreign recipes. The highest entropy in Korean recipes is the recipe, 'steamed frozen Pollack and seafood,' that a large number of ingredients is increasing the recipe entropy. On the other hand, the recipe, 'ginseng black chicken soup,' has the smaller number of ingredients than other recipes. But rare ingredients such as 'ginseng,' 'black chicken,' and 'hedysarum' are increasing the recipe entropy.

3.2 Recipe Similarity Graph

The similarity of two recipes is hard to define in general since the taste of foods is so subjective matter. For this, we define a new rigorous measure for recipes similarity. Generally speaking it is accepted that two recipes are considered similar if they share a lot of common ingredients. But the number of common ingredients between r_a and r_b is not sufficient measure without considering the frequency of ingredient. For example, most recipes require 'garlic,' 'salt,' or 'pepper,' especially in Korean cuisines. So we should consider these factors. Our ingredient entropy would be a good measure for the similarity of recipes by considering the rarity of ingredients. We know that an ingredient,



(a)



(b)

Figure 3. Frequency distribution of **(a)** the ingredient entropies and **(b)** the recipe entropies.

'truffle mushroom,' is so rare and expensive. If any two recipes r_x and r_y require this truffle, then the subjective taste or people preference on the foods from r_x and r_y will be similar. So the proposed $sim(r_x, r_y)$ will be one universal similarity of two recipes r_x and r_y in the following.

$$sim(r_x, r_y) = \sum_{i_k \in \{r_x \cap r_y\}} E(i_k) \quad (7)$$

We can construct the recipe graph $G_R(V, E)$ by making $edge(r_x, r_y)$ between two recipes r_x and r_y if $sim(r_x, r_y) > t_0$ for a threshold t_0 given, where V = R. $G_R(V, E)$ will be denser (sparser) if t_0 is high (low).

Table 4 shows the similarities between recipes and ranking of the similarities. The similarity is calculated by summing up the entropies of common ingredients between two recipes. When two recipes have more number of the common ingredients or more number of the rare common ingredients, the similarity will be increasing. In the similarities between countries, Korean recipes and Chinese recipes showhigh similarity and others are low.

Figure 4 shows the frequency distribution of the similarity of two recipes. Most similarity degrees between two recipes are low, from 0 to 10.

To understand the relation among all recipes, we constructed the recipe network that is based on the similarity of recipe pairs that can be calculated using Equation 7. We used the minimum spanning tree to connect the most similar recipes. The minimum span-

Table 3. The entropy of recipes and the number of ingredients

Ranking	Korean recipes			Foreign recipes		
	recipe	entropy	# of ingredients	recipe	entropy	# of ingredients
1	Steamed frozen pollack and seafood	74.79	27	Vegetarian lasagna	58.59	23
2	Bulgogi burger	59.84	20	Thai salad	56.72	18
3	Shrimp fried rice	50.24	16	Lasagna	49.59	20
4	Jumbo sized buckwheat noodles	49.69	21	Spicy szechuan beef	48.84	24
5	nutritious seafood rice	48.60	17	Italian bread salad	48.50	17
6	Ginseng black chicken soup	47.49	11	Italian ribollita	48.33	16
7	Sweet and sour yellow corvina	46.60	21	Cuscuz	46.98	15
8	Pig's feet and vegetables	46.26	16	California walnut spring rolls	45.74	20
9	Sujebi and crab stew	45.81	22	Thai chicken burger	45.63	17
10	Fusion noodles	44.82	14	Asparagus and trout risotto	45.24	18

Table 4. Ranking of similarity degree between recipes

Ranking	Korean recipes			Foreign recipes			Total recipes		
	recipe	recipe	*sim*	recipe	recipe	*sim*	recipe	recipe	*sim*
1	Egg and sea cucumber soup	Stir-fried pork with pepper	26.66	Chinese tofu[2]	Stir-fried chicken with hot sauce[2]	32.46	Chinese pork meatball[2]	Sweet and sour yellow corvina[1]	33.28
2	Fish ball soup	Vegetable and tofu soup	24.39	Chinese pork meatball[2]	Stir-fried chicken with hot sauce[2]	30.03	Chinese tofu[2]	Stir-fried chicken with hot sauce[2]	33.18
3	Egg and sea cucumber soup	Fish ball soup	23.85	Chinese tofu[2]	Chinese pork meatball[2]	27.89	Chinese pork meatball[2]	Stir-fried chicken with hot sauce[2]	32.23

(*Continued*)

Table 4. Continued

Ranking	Korean recipes			Foreign recipes			Total recipes		
	recipe	recipe	*sim*	recipe	recipe	*sim*	recipe	recipe	*sim*
4	Stir-fried pork with pepper	Fish ball soup	23.85	Stir-fried chicken with hot sauce[2]	Spicy szechuan beef[2]	26.84	Chinese tofu[2]	Chinese pork meatball[2]	29.38
5	Steamed frozen pollack and seafood	Korean spicy chicken	23.44	Spicy szechuan beef[2]	Stir-fried pork in black bean sauce[2]	25.88	Cucumber spring roll[2]	Egg and sea cucumber soup[1]	28.95
6	Sweet and sour yellow corvina	Stir-fried pork with pepper	23.11	Chinese tofu[2]	Stir-fried pork in black bean sauce[2]	25.70	Rosemary herbed pork cutlet[3]	Mozzarella pork cutlet[3]	27.99
7	Egg and sea cucumber soup	Sweet and sour yellow corbina	22.97	Chinese tofu[2]	Spicy szechuan beef[2]	25.45	Chinese stir-fried vegetable[2]	Spicy szechuan beef[2]	27.88
8	Sweet and sour yellow corvina	Fried shrimp with ketchup	22.48	Stir-fried chicken with hot sauce[2]	Stir-fried pork in black bean sauce[2]	24.75	Stir-fried chicken with hot sauce[2]	Spicy szechuan beef[2]	27.79
9	Pig's feet and vegetables	Jumbo sized buckwheat noodles	21.07	Chinese stir-fried vegetable[2]	Spicy szechuan beef[2]	24.65	Stir-fried chicken with hot sauce[2]	Fish ball soup[1]	27.70
10	Sauteed leek and pork	Stir-fried pork with pepper	21.05	Mapo tofu[2]	Spicy szechuan beef[2]	24.14	Stir-fried chicken with hot sauce[2]	Sweet and sour yellow corvina[1]	27.58

(1 Korean recipes, 2 Chinese recipes, 3 Japanese recipes, 4 Thailand recipes, 5 Italian recipes)

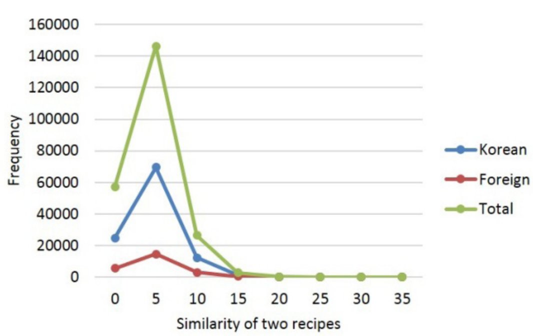


Figure 4. Frequency distribution of the similarity degree between recipes.

ning tree is a graph algorithm to connect all vertices through edges with the lowest cost[18,19]. In this paper, we first connected the recipes with the highest similarity and continued until all of the recipes are connected. Figure 5 shows the minimum spanning tree of recipe similarity network.

Figure 5 shows that recipes are well clustered in terms of national cuisine style. Italian recipes (yellow diamond shape) and Chinese recipes (green triangle shape) are very closed in network respectively. From this result, we can know that the recipe similarity based on the ingredient entropy reflects the characteristics of the recipe.

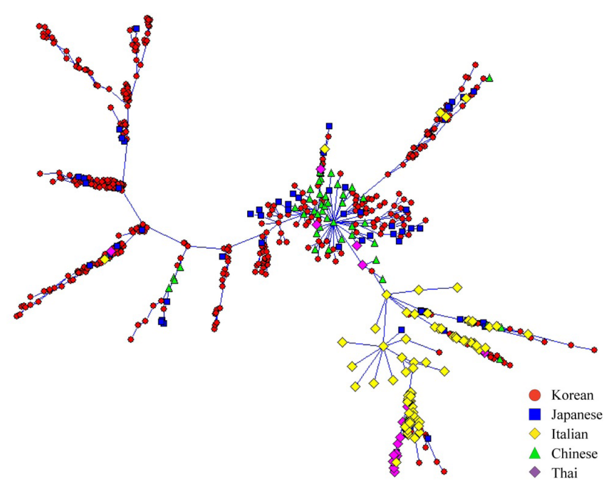


Figure 5. Minimum spanning tree of the recipe similarity network.

3.3 Ingredient Relation Graph

In a similar way, we can compute the relatedness of two ingredients i_x and i_y in a recipe r_k. If two ingredients occur in a recipe, then we say two ingredients are related in some manner. This relatedness can be measured relatively compared to other ingredients in a recipe r_k as follows $Imp_{r_k}(i_x, i_y)$. The importance of two co-occurrence ingredients based on a specific recipe r_k, $Imp_{r_k}(i_x, i_y)$, is defined the proportion of sum of two entropies compared with the total ingredient entropy sum.

$$Imp_{r_k}(i_x, i_y) = \frac{E(i_x) + E(i_y)}{\sum_{i_k \in R} E(i_k)} \tag{8}$$

Using $Imp(\square)$, we define $Rel(i_x, i_y)$, the relation degree of two ingredients i_x and i_y over all recipes R in the following.

$$Rel(i_x, i_y) = \sum_{r_x \in R} Imp_{r_k}(i_x, i_y) \tag{9}$$

This $Rel(i_x, i_y)$ weight enable us to construct the ingredient graph $G_I(V, E)$ such that the vertex set $V(G_I) \equiv 1$ and $edge(i_x, i_y)$ is given if $Rel(i_x, i_y) > t_q$ which prevent $G_I(V, E)$ to dense by removing some weak edges in terms of ingredients relation. It is easy to see that $Rel(i_x, i_y)$ of two ingredients is higher when i_x and i_y co-occurs more frequently in recipes. Also, the relative importance of i_x and i_y in a single recipe will affect $Rel(i_x, i_y)$. Though the pair of 'garlic' and 'scallion' co-occurs more frequently than any pairs, $Rel(garlic, scallion)$ is not so higher than what we expect since the importance of garlic and scallion, $Imp_w(garlic, scallion)$, is not high. There are lots of other ingredients in any recipes and the entropies of garlic and scallion are low. It is general to see the following.

$$Imp_w(sesame, sesame\ oil) > Imp_w(garlic, scallion) \tag{10}$$

Table 5 shows the 375 ingredient pairs, i_x and i_y, used in 683 recipes with high relation degree. In Korean recipes, the pair of 'sesame' and 'sesame oil' has the highest relation degree and they appear together in 116 recipes of 465 Korean recipes. These ingredients are used almost together in Korean cooking. The number of recipes including 'sesame' and 'sesame oil' is lower than the number of recipes including 'garlic' and 'scallion', but the importance of 'sesame' and 'sesame oil' is higher. In foreign recipes, 'salt' and 'pepper' has the highest relation and they appear together in 71 recipes of 218 foreign recipes. The ingredients, 'sesame', 'sesame oil', 'garlic', 'scallion' and 'soy source', are very closely related in foods.

Figure 6 shows the ingredient relation network using the minimum spanning tree where a node represents an ingredient. The ingredient graph consists of 375 prototype ingredients used in 683 recipes. The ingredients in the center of the network, 'garlic,' 'soy sauce,' 'scallion', 'sesame oil', 'salt',

Table 5. Highly-linked ingredient pairs

Ranking	Korean recipes				Foreign recipes				Total recipes			
	i_x	i_y	$Rel(i_x, i_y)$	# of recipes	i_x	i_y	$Rel(i_x, i_y)$	# of recipes	i_x	i_y	$Rel(i_x, i_y)$	# of recipes
1	sesame	sesame oil	12.74	116	salt	pepper	4.86	71	sesame	sesame oil	15.42	120
2	garlic	scallion	12.51	182	soy sauce	cooking oil	4.21	41	garlic	scallion	15.13	219
3	garlic	soy sauce	11.49	162	soy sauce	scallion	4.21	44	garlic	soy sauce	14.38	206
4	sesame oil	soy sauce	11.09	125	olive oil	garlic	3.72	44	sesame oil	soy sauce	14.13	148
5	garlic	sesame oil	11.01	144	soy source	ginger	3.70	35	garlic	sesame oil	13.77	169
6	garlic	sesame	10.78	119	olive oil	cheese	3.58	23	scallion	soy sauce	13.08	165
7	chili powder	garlic	10.68	114	onion	pepper	3.55	43	garlic	sesame	12.76	125
8	scallion	sesame oil	9.71	110	olive oil	tomato	3.54	25	scallion	sesame oil	12.72	133
9	sesame	soy sauce	9.64	96	scallion	cooking oil	3.42	35	garlic	chili powder	12.47	127
10	scallion	sesame	9.62	89	pepper	garlic	3.39	55	soy sauce	sugar	11.92	125

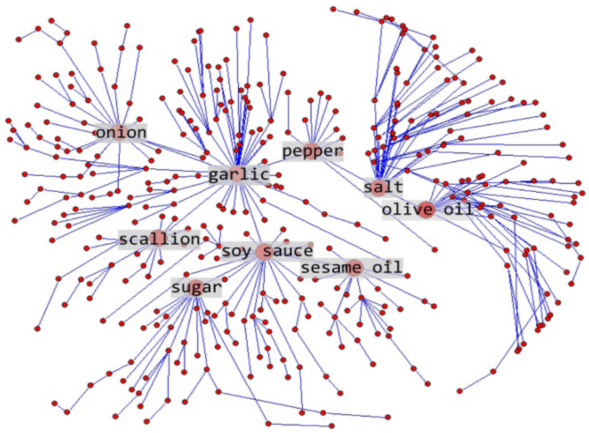


Figure 6. Minimum spanning tree of the ingredient relation network.

'olive oil', 'sugar', 'onion' and 'pepper' are typical ingredients closely related with other ingredients. For example, if 'ginger', 'hot pepper' and 'chili powder' are included in a recipe, 'garlic' is almost essential in this recipe.

4. Conclusion

In this paper, we proposed a quantitative method to calculate the relation of ingredients and recipes using entropy measure. And we constructed a recipe similarity network and an ingredient relation network based on social network paradigm to what foods are similar and what ingredients are highly related.

We used the probability to measure the entropy of ingredients and recipes. If any ingredient such as 'garlic' is used in almost foods, its probability is very high and its entropy is very low. The entropy of a recipe will be increasing if a recipe has more rare ingredients. Because the rarer ingredient has a higher entropy degree.

We analyzed the similarity of recipes measured by the entropy of common ingredients in recipes and the relation of the ingredients that co-occurs in recipes. Finally, we constructed a recipe network that connects the recipes having high similarity using the minimum spanning tree and an ingredient network that shows the correlations of ingredients in recipes. In the experiment, the recipe similarity network shows that recipes are well clustered in terms of national cuisine style and the entropy measure is a method to present well the similarity between recipes.

In future work, we plan to extend recipe similarity not only using ingredients but also using the cooking procedure in a recipe. The cooking procedure is one of the important information in a recipe and cuisine style is influenced by cooking method. For example, 'Stir-fried pork with pepper' in Korean recipes is actually Chinese food and the cooking procedure is similar with Chinese recipes. We expect to obtain better clustering result by considering various factors included in a recipe.

5. Acknowledgment

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