Hiroshima City University at NTCIR-11 Cooking Recipe Search Task

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ABSTRACT
Our group participated in the subtask involving an ad hoc Japanese recipe search. Our goal was to evaluate the effectiveness of our Japanese cooking ontology for the recipe search. To investigate the effectiveness of our ontology-based approach, we conducted experiments and found that our method can improve upon traditional document retrieval systems.

Keywords
ontology, synonym, query expansion

1. INTRODUCTION
There has recently been an increase in research work focusing on cooking recipes, including recommendation [7], summarization [8], and predicate-argument structure analysis [5]. However, different terms appear in different recipes, particularly in user-generated recipe-sharing sites, even though these terms often refer to the same thing. We have therefore constructed a cooking ontology that can be used in a variety of language processing tasks as a linguistic resource [6]. Our goal in NTCIR-11 [9] was to evaluate the effectiveness of our ontology for the recipe search.

This paper is organized as follows. Section 2 explains the method for constructing a cooking ontology. Section 3 contains a system description. To investigate the effectiveness of our method, we conducted experiments, as reported in Section 4. We present our conclusions in Section 5.

2. A JAPANESE COOKING ONTOLOGY
2.1 Overview of Our Cooking Ontology
The structure of our cooking ontology is shown in Figure 1. Our ontology employs a two-level hierarchy. The top level comprises the following seven categories.

- Ingredient - seafood
- Ingredient - meat
- Ingredient - vegetable
- Ingredient - other
- Condiment
- Kitchen tool
- Movement

Among these categories, “Movement” is a category involving verbs, while the others involve nouns. Each category contains several entry words. For example, in Figure 1, the ingredient-seafood category comprises several entry words such as “squid” and “shrimp.” For each entry, several related terms are classified into three categories: “synonymy,” “meronymy,” and “attribute.” Among these categories, we used synonymy relation for the recipe search. In the following section, we will introduce (1) determination of entry words and (2) collection of synonyms for each entry word in Sections 2.2 and 2.3, respectively. We also show the statistics of our ontology in Section 2.4.

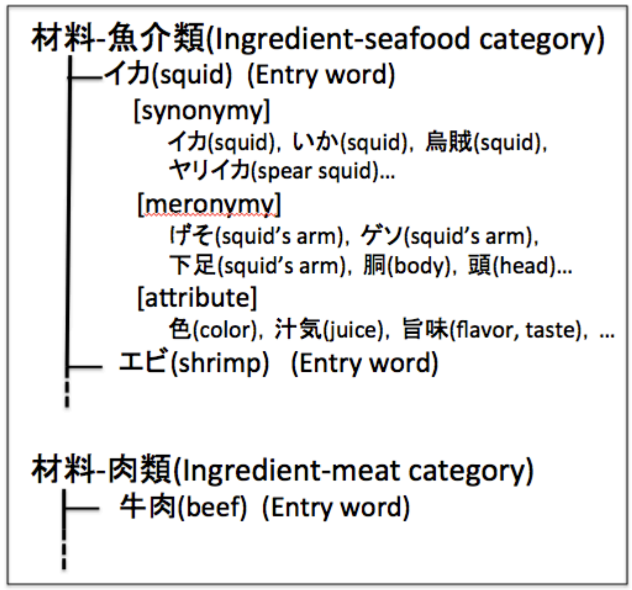

Figure 1: Structure of Our Cooking Ontology.

2.2 Determination of Entry Words
We determined entry words via the following two substeps.

(Step 1-1) Collecting candidate words from patents
(Step 1-2) Selecting entry words manually

In Step 1-1, we applied Hearst’s method [2] to patents[1], and collected candidates for entry words. For the following five categories, we prepared seed words that were synonyms of each category name, and then collected hyponyms using the pattern “NP_0 ((、|や)NP_n)* (等|など)の[seed word]” ([seed word] such as NP_0 ((,|and|or) NP_n)*).

- Ingredient – seafood
  魚類(fish), 魚介類(fish), 海産物(sea product), 水産物(fishery product)
- Ingredient – meat
  肉類(meat), 食肉(edible meat), 食肉類(edible meat), 原料肉(ingredient meat)

[1] We used those unexamined Japanese patent applications over 19 years (1993-2011) to which any of the International Patent Classification codes A23L (foods, foodstuffs, or non-alcoholic beverages), A47J (kitchen equipment), or H05B (electric heating, electric lighting) were assigned.

- Ingredient – vegetable
  野菜(vegetable)，果菜類(fruit vegetable)，野菜類(vegetable)，果菜物(fruit vegetable)，農産物(agricultural products)
- Condiment
  調味料(condiment)，香辛料(spice)，薬味(condiment)，スパイス類(spice)
- Kitchen tool
  調理器具(kitchen tool)，調理容器(cooking container)，調理器(cooking device)，調理具(cooking tool)，調理道具(cooking utensil)

For example, when we collected candidate words for the ingredient-seafood category, we found sentences that contained patterns such as “(NP_0 ((、|や)NP_n)*)などの魚類” (fish such as ((,|and|or) NP_n)*)) or “(NP_0 ((、|や)NP_n)*)等の水産物” (fishery product such as ((,|and|or) NP_n)*)). We then extracted noun phrases (NP_0 and NP_n), such as “イカ” (squid) or “エビ” (shrimp), as candidates for entry words in the ingredient-seafood category.

Although Hearst’s pattern-based method is useful for collecting hyponyms from texts, there are several cases where inappropriate words are mistakenly extracted. In the following sentence, “食用” (edible use) and “鑑賞用” (ornamental purpose) are mistakenly extracted as candidates for the ingredient-seafood category.

食用や観賞用等の魚介類をいう。
(This indicates fish for edible use and for ornamental purposes)

We therefore delete such inappropriate words manually from the candidate list in Step 1-2. From among the remaining candidates, we statistically determined one representative word for each group of synonyms. As an example, for the three candidates “サケ” (salmon), “鮭” (salmon), and “さけ” (salmon), we manually selected “サケ” as the representative word, because the frequency of the phrase “サケ(など|等)の魚介類” (fish such as a salmon) is greater than those of “鮭(など|等)の魚介類” (fish such as a salmon) and “さけ(など|等)の魚介類” (fish such as a salmon).

We selected ingredient words that do not belong to any of the ingredient-seafood, -meat, and -vegetable categories as entry words in the ingredient-other category. Most of the words in this category are processed foods, such as cheese and pasta.

For entry words in the movement category, we manually selected verbs appear frequently in the Rakuten Data provided by Rakuten, Inc.

2.3 Collection of Synonyms for Each Entry Words

The procedure of collecting synonyms for each entry word comprises the following two substeps.

(Step 2-1) Collecting candidates for synonyms.
(Step 2-2) Identifying synonyms manually.

In Step 2-1, we used the following three methods.

(Method 1) Using words that were deleted in the process of determining representative words in Step 1-2
(Method 2) Chung’s method [1]
(Method 3) Distributional similarity method [3, 4]

We have already described Method 1. Here, we explain Methods 2 and 3. Chung [1] proposed a method for extracting synonyms based on a recipe data structure. From the observation that the main ingredient is usually written first in the ingredient list of a recipe, he assumed that this first ingredient is strongly related to the category to which the recipe belongs. They confirmed experimentally that his method for calculating relation scores between ingredients and category names using the ingredient position was effective for collecting synonyms from a recipe database. We use this method to extract synonyms.

As we explained in the section on related work, the basic idea of distributional similarity is to calculate the similarity between two words in terms of their context words. Our algorithm is as follows.

1. Analyze the dependency structures of all sentences in the Rakuten Data, which contains about 440,000 recipes, using the Japanese parser CaboCha[2]
2. Extract <noun phrase><verb> pairs that have dependency relations from the dependency trees obtained in Step 1
3. Count the frequencies of each <noun phrase><verb> pair
4. Collect verbs and their tf*idf scores for each noun phrase, creating indices for each noun phrase
5. Calculate the similarities between two indices for noun phrases using the cosine distance
6. Obtain a list of synonymous noun phrases

In addition to collecting verbs for each noun phrase in Step 4 of the algorithm, we collected noun phrases for each verb similarly, obtaining a list of synonymous verbs.

In Step 2-2, we selected synonyms from the candidates obtained using the three methods. The characteristics of these methods are summarized in Table 1. We checked all candidates collected by Methods 1 and 2, because the numbers of candidates were small. The candidates collected by Method 3 were checked in order of similarity to each other as much as possible.

Table 1. Characteristics of the Three Methods Used for Collecting Synonyms.

	Reliability	**Number of candidates**	**Target category**
Method 1 (Deleted words in Step 1-2)	Fully reliable	Very small	All
Method 2 (Chung)	Highly reliable	Small	Except for “Movement”
Method 3 (distributional similarity)	Moderately reliable	Very large	All

2.4 Statistics of Entry Words and Synonyms

In Table 2, we show the numbers of entry words that were collected using the method mentioned in the previous section.

[2] https://code.google.com/p/cabocha/

Table 2. The Number of Entry Words for Each Category.

Category	Number of entry words
Ingredient - seafood	61
Ingredient - meat	6
Ingredient - vegetable	122
Ingredient - other	55
Condiment	51
Kitchen tool	48
Movement	131
Total	474

In Table 3, we show the numbers of synonyms for each category together with the number of synonyms for each entry word.

Table 3. The Number of Synonyms for Each Category.

Category	The number of synonyms (per each entry word)
Ingredient - seafood	453 (7.4)
Ingredient - meat	383 (63.8)
Ingredient - vegetable	947 (7.8)
Ingredient - other	732 (13.3)
Condiment	909 (17.8)
Kitchen tool	643 (13.4)
Movement	956 (7.3)
Total	5,023 (10.6)

3. SYSTEM DESCRIPTION

Our system comprises the following two steps:

(Step 1) Morphological analysis

We introduce a vector space model as the retrieval model and use Solr[3] as the retrieval engine. Here, each recipe in the Rakuten Data comprises the following items.

- A title
- A list of ingredients
- Procedures
- Three levels of category (1st, 2nd, and 3rd levels)
- Three tags (tags 1, 2, and 3)
- An explanation of the recipe
- Know-how information

We use one or more of these items to create an index of each recipe, which we will describe in more detail in Section 4.2.

[3] http://lucene.apache.org/solr/

(Step 2) Ontology-based query expansion

We expand queries using the synonyms obtained in Section 2.

4. EVALUATION

We used 500 Japanese queries for the ad hoc subtask to evaluate our method. All the systems were evaluated in terms of mean average precision (MAP).

4.1 Submitted Systems

We submitted the results produced by two systems: "HCU-JA1-BASE-01" and "HCU-JA1-TEST-01." Each system used a title, a list of ingredients, and procedures for creating an index for each recipe. The difference between these systems is that "HCU-JA1-TEST-01" used the ontology-based query expansion. We show the official results in Table 4.

Table 4. Official Results for Our Systems.

Systems	MAP	MRR	nDCG@10
HCU-JA1-BASE-01	0.0706	0.0763	0.1441
HCU-JA1-TEST-01	0.0667	0.0700	0.1441

After we submitted the results, we found some parameter setting errors when combining multiple items. We therefore conducted some additional experiments as reported in the following subsections.

4.2 Identification of the Best Combination of Items

We constructed the following 11 systems to enable identification of the best combination of items, using items listed in Step 1 of Section 3. In this examination, we did not use the ontology-based query expansion.

- TITLE: Create an index using a title.
- ING: Create an index using a list of ingredients.
- PROC: Create an index using a procedure.
- TAG1: Create an index using tag 1.
- TAG2: Create an index using tag 2.
- TAG3: Create an index using tag 3.
- CATEGORY1: Create an index using the 1st category level.
- CATEGORY2: Create an index using the 2nd category level.
- CATEGORY3: Create an index using the 3rd category level.
- EXP: Create an index using the explanation of the recipe.
- KNOW-HOW: Create an index using know-how information.

We examined each of these systems in terms of the dataset of the ad hoc subtask. The experimental results are shown in Table 5.

Table 5. Evaluation Results for 11 Systems Using a Single Item.

Method	MAP	Method	MAP
ING	0.5734	TAG3	0.0056
PROC	0.2110	CATEGORY3	0.0049
TITLE	0.1950	KNOW-HOW	0.0013
EXP	0.0423	CATEGORY2	0.0004
TAG1	0.0148	CATEGORY1	0.0000
TAG2	0.0074		

In the next step, we combined items that obtained top-n MAP scores. In combining these multiple items, we gave the same words appeared in different items the same weight. The results are shown in Table 6.

Table 6. Evaluation Results for Combinations of Some Items.

Method	MAP
ING	0.5734
ING+PROC	0.5736
ING+PROC+TITLE	**0.7518**
ING+PROC+TITLE+EXP	0.7277
ING+PROC+TITLE+EXP+TAG1	0.5271

As can be seen from Table 6, the combination of ING+PROC+TITLE obtained the best MAP score. For this combination, we also examined a variety of weights. We considered the MAP scores in Table 5 to be the reliability scores of each item, and employed these scores as weights of each field; that is, we employed weight values of 0.5734, 0.2110, and 0.1950 for ING, PROC, and TITLE, respectively. We examined the combination of ING, PROC, and TITLE using these weights, and obtained a MAP score of 0.7156, which is lower than the result of ING+PROC+TITLE in Table 6. We therefore used the combination of ING, PROC, and TITLE items with the same weighting for each item in the next step; namely, the ontology-based query expansion.

4.3 Ontology-based Query Expansion

We constructed the following five methods using the ING+PROC+TITLE method, which had obtained the best performance, as described in Section 4.2.

- SEAFOOD: Query expansion using synonyms in the ingredient-seafood category
- MEAT: Query expansion using synonyms in the ingredient-meat category
- VEGE: Query expansion using synonyms in the ingredient-vegetable category
- SEAFOOD+MEAT+VEGE: Query expansion using synonyms in the ingredient-seafood, -meat, and -vegetable categories
- SEAFOOD+MEAT+VEGE+CONDI: Query expansion using synonyms in the ingredient-seafood, -meat, -vegetable, and condiment categories

In this examination of these five methods, we employed the number of retrieved relevant documents within the top-100 results as another evaluation measure for investigating the effects of our ontology-based query expansion approach.

The results are shown in Table 7. Here, BASELINE indicates the ING+PROC+TITLE method of Table 6. As can be seen from Table 7, we can confirm that VEGE is useful for improving the MAP score of the BASELINE system. Although the MAP score of the SEAFOOD+MEAT+VEGE method was lower than the BASELINE method, the number of retrieved relevant documents was slightly improved.

Table 7. Evaluation Results of Ontology-based Query Expansion.

Method	MAP	The number of retrieved relevant documents within the top-100 results
SEAFOOD	0.7508	**601**
MEAT	0.7306	594
VEGE	**0.7635**	596
SEAFOOD+MEAT +VEGE	0.7406	**603**
SEAFOOD+MEAT +VEGE+CONDI	0.6858	587
BASELINE	0.7518	599

There is a reason that the VEGE method was an improvement on the BASELINE method, whereas both the MEAT and SEAFOOD methods were not. It is mainly a result of the policy used in constructing the ontology. Consider these two examples of synonyms for a carrot and a salmon.

- Synonyms of “carrot”: ニンジン (carrot), 金時ニンジン (Japanese red Kintoki carrot), にんじん (carrot), 人参 (carrot), キャロット (carrot)
- Synonyms of “salmon”: サケ (salmon), さけ (salmon), 鮭 (salmon), シャケ (salmon), しゃけ (salmon), 秋鮭 (autumn salmon), 紅鮭 (sockeye salmon), サーモン (salmon), キングサーモン (king salmon), サケフレーク (salmon flakes), さけフレーク (salmon flakes), 鮭フレーク (salmon flakes), シャケフレーク (salmon flakes), しゃけフレーク (salmon flakes), 塩鮭 (salted salmon), 生鮭 (raw salmon)

We can identify that some intermediate products, such as しゃけフレーク (salmon flakes) and 塩鮭 (salted salmon), are also a kind of synonym. The ratios of such intermediate products in the ingredient-meat and ingredient-seafood categories are larger than for the ingredient-vegetable category, and this can often cause a decrease in the MAP scores.

5. CONCLUSION

In this paper, we proposed an ontology-based query expansion for the subtask of ad hoc Japanese recipe search. One of our methods, namely VEGE, outperformed a baseline method ING+PROC+TITLE. From our results, we confirmed the effectiveness of our ontology for recipe search.

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