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Cooking Recipe Search by Pairs of Ingredient and Action — Word Sequence v.s. Flow-graph Representation —

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Summary

This paper proposes a method for searching cooking recipes by a procedure such as "a tomato is fried." Although most of methods for cooking recipe search treat recipe text as Bag-of-Words (BoW), it misdetects such a recipe that "fry an onion deeply and serve it with a tomato cube (in which the tomato is not heated)." Our method converts a procedural text to a flow-graph automatically in advance using a dependency parsing technique. In the flow-graph, action sequence that will be performed to an ingredient is easily extracted by tracing the path from the node corresponding to the ingredient to the root node corresponding to the last action. We evaluate our method comparing with a task adapted BoW model as a baseline and the proposed method achieved a precision of 68.8% while the baseline method achieved it of 61.5%.

1. Introduction

The number of recipes on the Web has been increasing rapidly in recent years. In the United States, "Food.com[*1]" has more than 475,000 recipes, while "Allrecipe[*2]" and "Foodnetwork[*3]" have more than 10 million users. Many web search services such as Google and Bing also provide tools for recipe search. In Japan, "Cookpad[*4]," one of the biggest recipe portal sites, has more than 2.3 million recipes and 12 million users. According to their corporate profile the number of recipes they have is still increasing linearly. Another Japanese recipe site, "Rakuten-Recipe[*5]," was launched in 2010 and has already acquired one million unique recipes. These Japanese recipes are provided for academic use under the support of the National Institute of Informatics (NII) in Japan[*6], and many researchers are using them to develop new approaches for cooking recipe search.

Although most cooking recipe search systems treat recipe text as a Bag-of-Words (BoW), this representation discards the word order that is crucial for establishing the order of actions described by a procedural text. Thus, recipes represented using the BoW approach cannot be searched by cooking procedures. Suppose that a user likes "cooked tomatoes" but not "fresh tomatoes," so

*1 http://www.food.com/
*2 http://allrecipes.com/
*3 http://www.foodnetwork.com/
*4 http://cookpad.com/
*5 http://recipe.rakuten.co.jp/
*6 Cookpad data set: http://www.nii.ac.jp/dsc/idr/cookpad/cookpad.html, Rakuten data set: http://www.nii.ac.jp/dsc/idr/rakuten/rakuten.html

Table 1 Recipe named entity tags.

NE tag	Meaning	NE tag	Meaning
F	Food	Ac	Action by a chef
T	Tool	Af	Action by foods
D	Duration	Sf	State of foods
Q	Quantity	St	State of tools

he searches for a recipe using the query “tomato & fry.” Even if a recipe includes both the words “tomato” and “fry,” it does not necessarily mean that the tomatoes are fried; the recipe may direct us to “fry other ingredients and serve them with fresh tomato cubes.” Initially, a simple approach based on word order may seem attractive because it can be used to infer that “tomatoes are not fried” if the word “fry” appears much earlier than the word “tomatoes.” However, a recipe describes a partial ordering of cooking actions that includes parallel processes, so tracing the procedural flow can give drastically different results compared to a simple analysis based on word ordering.

In our method, the system first uses dependency parsing to convert the procedural text of each recipe into a flow graph that represents the cooking workflow. Note that our method takes the sequence of sentences of the recipe text as the input, but not a single sentence in the normal dependency parsing case. It then extracts the action sequence that will be performed on each given ingredient by tracing the flow graph. Even though the F-measure of the dependency estimation is only 78.3, which is considered insufficient for general purposes, we show that this automatically converted flow graph is more effective than the BoW model for the task of searching recipes by ingredient and action pairs.

2. Recipe Flow Graphs

It has been shown that the meaning of a procedural text can be represented as a flow graph for Japanese recipe [Mori 14]. The flow graph is a directed acyclic graph with a root (or a rooted DAG). Its nodes correspond to important terms, which are recipe named entities (r-NE) in the case of recipes that are defined in [Mori 14]. Table 1 lists r-NE tags and their meanings. Edges of the graph denote the relationship between r-NEs[*7]. Figure 1 shows a recipe text example[*8]. This figure focuses on the r-NEs for ingredients (F = Food) and actions taken by a chef (Ac = Action by a chef), which are placed in boxes with solid lines. Other types of r-NEs are in boxes with dotted lines. Figure 2 shows the flow graph of this recipe. As you can see, it is obvious which actions are applied to which ingredients. For example, just by following the edges from the boiled egg in Figure 2, we can see that we do not mash it but this is not obvious in the text shown in Figure 1.

As shown above, the flow graph representation is useful for understanding recipes. However, because we cannot expect recipe writers to draw flow graphs, we need an automatic conversion method. There have been some attempts at building a flow graph from a recipe text. Maeta et al. [Maeta 15] have proposed to divide the problem into three steps: word segmentation (needed because Japanese is written without word boundaries), r-NE recognition, and flow graph construction. Machine learning techniques are used to solve each step. For the first two tasks, we can use the same publicly available tools[*9]. For the last step, we implemented a flow graph constructor. We tested it on the recipe flow graph corpus[*10]. As reported in [Maeta 15], the accuracy is 72.1, or 78.3 if we ignore the edge labels. In this paper we choose to ignore the edge labels.

The recipe search method that we propose in the subsequent sections runs on the automatically constructed flow graphs, though thye does contain produce some errors.

3. Procedural Recipe Search Algorithm

3·1 Task Setting

Assume that a user wants to search for a dish where a specific ingredient is cooked using a specific action. For example, he wants to find a recipe where a boiled egg is mashed because his children do not like eggs but he still wants them to eat eggs. In this case, the user combines the ingredient and action and submits the query “boiled egg mash.” In the recipe dataset [Harashima 16], there are many recipes where something is mashed and that have boiled eggs, but few recipes where boiled eggs are mashed.

3·2 General Bag-of-Words Model

As a baseline method, general Bag-of-Words is introduced. Hereafter, we call it as “Gen.BoW.” The system extracts the words recognized as actions taken by a chef, which are labeled as “Ac” by r-NE recognition, from a procedural text and constructs a BoW. One recipe corresponds to one Gen.BoW. The system retrieves a recipe when it has the given ingredient and its BoW contains the

∗7 Though 13 different edge types are defined in [Mori 14], we do not use them in the proposed method.

∗8 This recipe was taken from `http://cookpad.com/recipe/2668179` “簡単☆レンジでポテトサラダ” by ルナＰボール.

∗9 Word segmentation: `http://www.phontron.com/kytea/`. NE recognition: `http://www.ar.media.kyoto-u.ac.jp/tool/PWNER/home-e.html`.

∗10 `http://www.ar.media.kyoto-u.ac.jp/data/recipe/home-e.html`

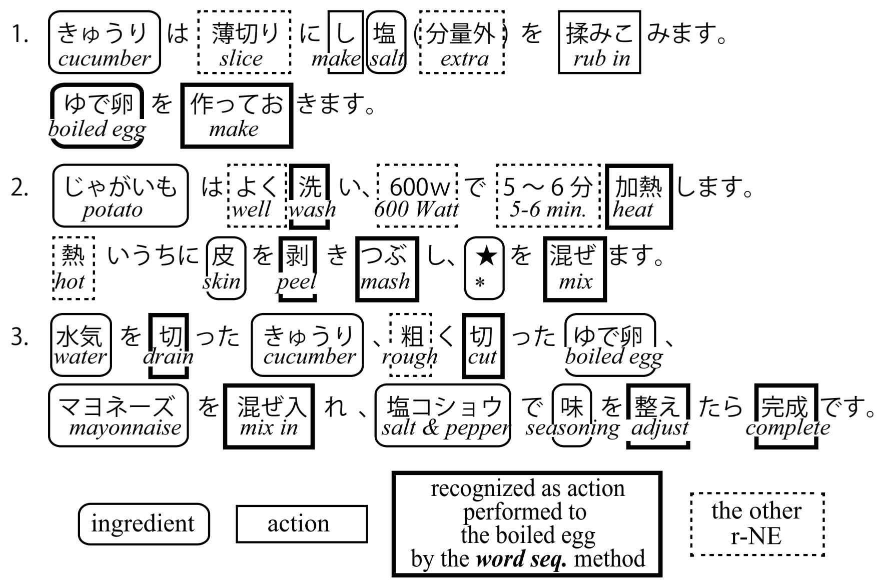

Fig. 1 An example of procedural text and the results after running the NLP system on it. Important terms defined in Table 1 are placed in boxes. Boxes with bold lines are the actions performed to the boiled egg (the rounded box in the first sentence) which were recognized by one of the baseline method “SubSent.BoW”.

given action. Using Figure 1 as an example, the system extracts the action set “し (make), 揉み込 (rub in), 作ってお (make), 洗 (wash), 加熱 (heat), 剥 (peel), つぶ (mash), 混ぜ (mix), 切 (drain), 切 (cut), 混ぜ入 (mix in), 整え (adjust), 完成 (complete)” as its Gen.BoW. When a user submits “ゆで卵 (boiled egg) 切 (cut)” as a qyery, the system correctry retrieves the recipe because it has “ゆで卵 (boiled egg)” as an ingredient and the Gen.BoW includes “切 (cut).” However, when a user submits “ゆで卵 (boiled egg) つぶ (mash)” as a query, the system wrongly retrieves it because its Gen.BoW includes “つぶ (mash).”

3·3 Sentence Bag-of-Words Model

Because actions described in the same sentence with an ingredient tend to be performed to the ingredient in general, we introduce a sentence BoW that is a set of action words included in each sentence and is labeled with the ingredients that appear in the same sentence. Hereafter, we call it as “Sent.BoW.” One recipe corresponds to multiple Sent.BoWs. A recipe is retrieved when it has the given ingredients and at least one Sent.BoW of the recipe labeled with the given ingredient contains the given action. Using Figure 1 as an example, the system extracts the action set composed “洗 (wash), 加熱 (heat)” as its Sent.BoW labeled with “じゃがいも (potato).” When a user submits “じゃがいも (potato) 加熱 (heat)” as a query, the system correctly retrieves the recipe because its Sent.BoW labeled with “じゃがいも (potato)” includes “加熱 (heat).” However, when a user submits “じゃがいも (potato) つぶ (mash)” as a query, the system wrongly excludes the recipe because the Sent.BoW labelled with “じゃがいも (potato)” does not include “つぶ (mash).”

3·4 Subsequent Sentence Bag-of-Words Model

As mentioned in the introduction, actions that appear much earlier than an ingredient in the description tend not to be performed to that ingredient. So the general BoW model can be improved by addressing only the subsequent sentences of the sentence in which the given ingredient first appears. Hereafter, we call it as “SubSent.BoW.” Using the example in Figure 1, when the user query is “ゆで卵 (boiled egg) つぶ (mash),” this improved BoW model skips the first sentence because the given ingredient “ゆで卵 (boiled egg)” has not appeared yet, and constructs the BoW from the following sentences as “作ってお (make), 洗 (wash), 加熱 (heat), 剥 (peel), つぶ (mash), 切 (drain), 切 (cut), 混ぜ入 (mix in), 整え (adjust), 完成 (complete).” Since the actions included in the first sentence “し (make), 揉み込 (rub in)” are not performed to the given ingredient “ゆで卵 (boiled egg)”, it is said that this method correctly eliminates the false positive candidates. However, in this case, this model still causes a false positive because the action “つぶ (mash),” which is performed not to a boiled egg but to a boiled potato, appears in the following sentence.

3·5 Flow-Graph-based Method

When a flow graph is correctly converted from the procedural text, true action set that is performed to the given ingredient can be extracted by tracing the flow graph from the ingredient to the root, which corresponds to the final

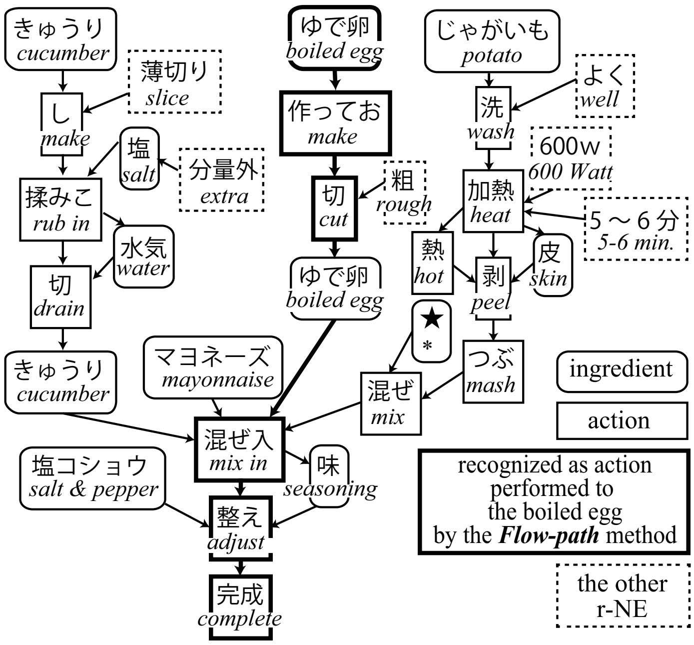

Fig. 2 The flow graph of the recipe shown in Figure 1. Important terms defined in Table 1 are placed in boxes. Boxes with bold lines are the actions performed to the boiled egg (the rounded box in the first sentence) which were recognized by the proposed method “Flow”.

action. Even though automatically converted flow graph contains some errors, we considered that this method is able to extract better action set closer to the truth than the methods mentioned above. Therefore, in the proposed method, the system converts a procedural text to a flow graph for each recipe in advance, and then it extracts action set for each ingredient by tracing from the ingredient to the root. Hereafter, we call it as “Flow.” When a user submits a set of a ingredient and actions as a query, it retrieves recipes where the action set corresponds to the given ingredient includes the given actions. Using Figure 2 as an example, when a user submits “ゆで卵 (boiled egg), つぶ (mash)” as a query, the proposed method can correctly exclude this recipe because the extracted action set “作ってお (make), 切 (cut), 混ぜ入 (mix in), 整え (adjust), 完成 (complete)” does not contain the given action “つぶ (mash).” This proposed method also gives grand truth when the flow graph is converted correctly from the procedural text.

3·6 Expansion of Available Query Variation

When a user submits a query composed of multiple pairs of an ingredient and an action such as both of “卵 (egg), 茹で (boil)” and “卵 (egg), つぶ (mash)” at the same time, each method firstly extracts search results by each of the query and then returns the intersection of them as the final results. When a user specifies a title of a served meal such as “サラダ (salada)” as a part of a query, each method firstly narrows down the target recipes into the recipes whose title includes the word “サラダ (salada),” and then it extracts the search results from them.

Table 2 Action sequence extraction accuracy.

	Precision	Recall	F-measure
Gen.BoW	40.6%	97.2%	57.3%
Sent.BoW	73.2%	27.8%	40.3%
SubSent.BoW	61.5%	97.0%	75.2%
Flow	68.8%	90.8%	78.3%

4. Experiments and Results

4·1 Extraction Accuracy of Ingredients and Action Combination

First, we evaluated the extraction accuracy of action set performed to each ingredient. Gold standard action set was obtained by the flow-graph-based method from the flow graph corpus that was manually translated from procedural texts [Mori 14]. The flow graphs are composed of 208 randomly selected recipes that include 1219 ingredients. On average, 6.8 actions are performed to each ingredient to complete the cooking.

We evaluated the methods as follows. Suppose R^i $(1 \leq i \leq 208)$ is a recipe in the corpus and ing^i_j is an ingredient used in the recipe R^i. The action set performed to ing^i_j in the gold standard is $\mathrm{Act\_true}^i_j$. The action set that is estimated to be performed to ing^i_j by a method is $\mathrm{Act\_estimated}^i_j$. The number of actions in an action set Act is represented as $\|\mathrm{Act}\|$. Then the precision, recall, and F-measure scores are calculated as follows;

$$\text{precision} = \frac{\sum_i \sum_j ||\text{Act\_true}^i_j \cap \text{Act\_estimated}^i_j||}{\sum_i \sum_j ||\text{Act\_estimated}^i_j||},$$

$$\text{recall} = \frac{\sum_i \sum_j ||\text{Act\_true}^i_j \cap \text{Act\_estimated}^i_j||}{\sum_i \sum_j ||\text{Act\_true}^i_j||},$$

$$\text{F-measure} = \frac{2 \cdot \text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}.$$

The results are shown in Table 2. Note that General Bag-of-Words method (Gen.Bow) does not achieve 100% recall because the word segmentation and r-NE recognition processes contain some errors.

As shown in the table, the proposed method achieved an F-measure of 78.3%, which was 3.1% higher than the second best, SubSent.BoW, and was much higher than the Gen.BoW method of 57.3%. Although SubSent.BoW achieved the best recall except for Gen.BoW, 97.0%, most people focus on only the top 10 results for search queries, so we favor a method that emphasizes high precision. Sent.BoW achieves the best precision but it has very low recall of 27.8%. Thus, we consider the proposed method more effective because its precision is 7.3% higher than SubSent.BoW.

4·2 Precisions of Search Results

We used our method on the "Cookpad data set [Harashima 16]" composed of 1.7 million recipes. We asked three people to propose queries according to the scenario mentioned in Section 3·1 and then 12 fictive queries were provided.

Firstly, we compared the flow-graph-based model with sentence BoW model which showed the best precision value. Figure 3 shows the percentages and the numbers of the recipes found by the flow-graph-based model only (Flow only), the sentence BoW model only (Sent only), and both methods (Both), respectively. According to this figure, these two methods still share almost half results but the other half results differ from each other. When an action of a given search query is the initial action toward an ingredient such as "peel," "cut," "chop," such action words tend to appear in the same sentence with the ingredient as "chop the carrot" and the sentence BoW method is able to find a lot of search result. However, when the given action is generally after the second or subsequence action toward the given ingredient as "fry," "mash," "heat by a microwave," such action words do not tend to appear in the same sentence with the ingredient but appear in the following sentences as "cut an onion. fry it in olive oil" and the sentence based method fails the extraction.

Then, we randomly selected 10 recipes from the results of the flow-graph-based model only (Flow only), the sentence BoW method only (Sent only) and the both methods (Both), respectively and manually evaluated their precisions. The precisions of these three categories are shown in Figure 4. The data is omitted from the graph for such queries that the numbers of the search results are less than 10. Although the results extracted by both of the flow-graph-based method and the sentence BoW method (Both) shows higher precisions than the results extracted by one of them (Flow only or Sent only) according to Figure 4, only limited number of search results were extracted by both of them according to Figure 3.

The most false results of the sentence BoW method only caused when a single sentence describes multiple combinations of ingredient and action. For example, when a sentence says "玉葱はみじん切りし，人参はレンジでチン (chop an onion, and heat a carrot by a microwave)," the sentence BoW method wrongly recognized the onion was heated by a microwave while the flow-graph-based method correctly recognized the ingredient "an onion" did not depend on the action "heated by a microwave."

Second, we compared the flow-graph-based model with the subsequent sentence BoW model which showed high recall and the second best F-measure value. Figure 5 shows the percentages and the numbers of the recipes found by the flow-graph-based model only (Flow only), the subsequent sentence Bag-of-Words model only (SubSent only), and both methods (Both), respectively. As shown in this figure, almost all the recipes found by the flow-graph-based method were also found by subsequent sentence BoW method, and 78.1% of the recipes found by the subsequent sentence BoW method were also found by the flow graph method.

Then, we randomly selected 10 recipes from the results of the subsequent sentence BoW method only (SubSent only) and the both methods (Both) respectively and manually evaluated their precisions. The precisions of these two categories are shown in Figure 6. The precision of both methods is equal or higher than the flow-graph-based method only and the sentence BoW method only at the all queries. The precision of the results extracted by both of them (Both) is clearly higher than that of the subsequent sentence BoW method only (SubSent only).

The flow-graph-based method takes an advantage when a cooking process of a recipe contained parallel processing. For example, when a chef cooks sea-food spaghetti, he cooks sauce and boils pasta at the same time. In this case, the recipe says "貝を洗って塩水につける．深めの鍋でパスタを茹でる． (wash the clams and dip them in salt water. boil a pasta in a deep pot)" and the subsequent sentence BoW misrecognized that the clams were boiled, while the flow-graph-based method can recognize that "wash and dip" and "boil" processes are promoting at the same time toward different foods.

On the other hand, converting a flow graph from such a parallel process description is also difficult NLP task and the flow graph method also fails when a wrong flow graph was generated. Since our flow graph conversion method tends to misrecognize parallel processes as a single process but tends not to do the opposite, the subsequent sentence BoW method also fails when the flow graph method fails.

For all methods, a negative sentence such as "taking care not to mash it up completely" cannot be recognized correctly.

Summarizing the experiments described above, we can say that (i) it has an advantage for a query when it is composed of an action which performed to the corresponding ingredient in later process of the cooking, and (ii) the flow-graph-based method is especially useful for rejecting false positives chosen by the subsequent sentence BoW method.

5. Related Work

The number of recipes on the Web has been increasing explosively in the last decade. So cooking recipe has been dealt with at various fields of research. Ahn et al. [Ahn 11] analyzed recipes and constructed a flavor network that captures the flavor compounds shared by culinary ingredients. They found Western cuisines tend to use ingredient pairs that share many flavor compounds while East Asian cuisines tend to avoid compound sharing ingredients. IBM's "Cognitive Cooking" project with Chef Watson[*11] generated new recipes by discovering new ingredient combination that share flavor compounds. In Japan, Cooking Recipe Search Task was embedded in the NTCIR-11 (NII Testbeds and Community for Information access Research) Project from 2013 to 2014 (`https://sites.google.com/site/ntcir11recipesearch/`). Both of English and Japanese recipe data and search topics were provided by Yummly (`http://www.yummly.com/`) and Rakuten-Recipe and many research groups joined and discovered new approaches. From the beginning of the field of artificial intelligence, recipes have been regarded as a typical case-based reasoning task. As far as we know, the first computational method for generating new recipes was proposed by Hammond [Hammond 86]. Recently, AI research groups have held the Computer Cooking Contest (`http://ccc2015.loria.fr/`) in conjunction with the international conference on case-based reasoning (ICCBR) from 2008, and many novel systems such as WikiTAAABLE [Badra 09] and CookIIS [Ihle 09] were proposed for the purpose of realizing intelligent cooking advisors. While we focus on Japanese recipes and adopted structure analysis method for Japanese ones, structure analysis for English recipes were also proposed by Kiddon et al. [Kiddon 15] and Jermsurawong and Habash [Jermsurawong 15].

Because recipe ingredients are closely linked to nutrition and calories, most recipe search methods focus only on the ingredient list [Ahn 11, Kuo 12, Tsukuda 10, Ueda 14, Varshney 13]. Druck and Pang [Druck 12] proposed a method that discovers refinements of a recipe from the reviews submitted by users who have used it to cook. Wang et al. [Wang 08] proposed a graphical representation of the cooking procedure, called a "cooking graph," in which ingredients and actions are modeled as nodes, which are connected by directed edges that indicate the ingredient and cooking flows. Then Xie et al. [Xie 10] proposed a recipe search method based on the cooking graph representation. Even though the cooking graph contains rich information, it must be built manually from recipe text. Ding et al. [Ding 13] proposed a method to improve web search ranking by detecting structure of a query. When a user submits "baking bread" as a query, their method recognizes "baking" is *directions* and "bread" is *ingredients* without using the structure of the target text.

6. Conclusion

Traditional NLP modeling incurs high costs of corpus construction, language model training, and parsing. Bag-of-Words modeling is often proposed as a simpler alternative that delivers better performance at a fraction of the cost. In this paper we focused on recipes, and showed that our NLP-based search method has big advantage on procedural text when we want to find specific types of recipes, such as recipes where tomatoes are cooked.

In this recipe search task, the query is provided not as a set of words, but as a procedure. Our method automatically generates a flow graph for a recipe, and extracts action sequences performed to ingredients by tracing the path from the node corresponding to the ingredient to the root node corresponding to the last action in the graph. The proposed method achieved a precision of 68.8%, which is much higher than that of the improved BoW method, 61.5%. We plan to release this system as a

*11 `http://www.ibm.com/smarterplanet/us/en/cognitivecooking/`

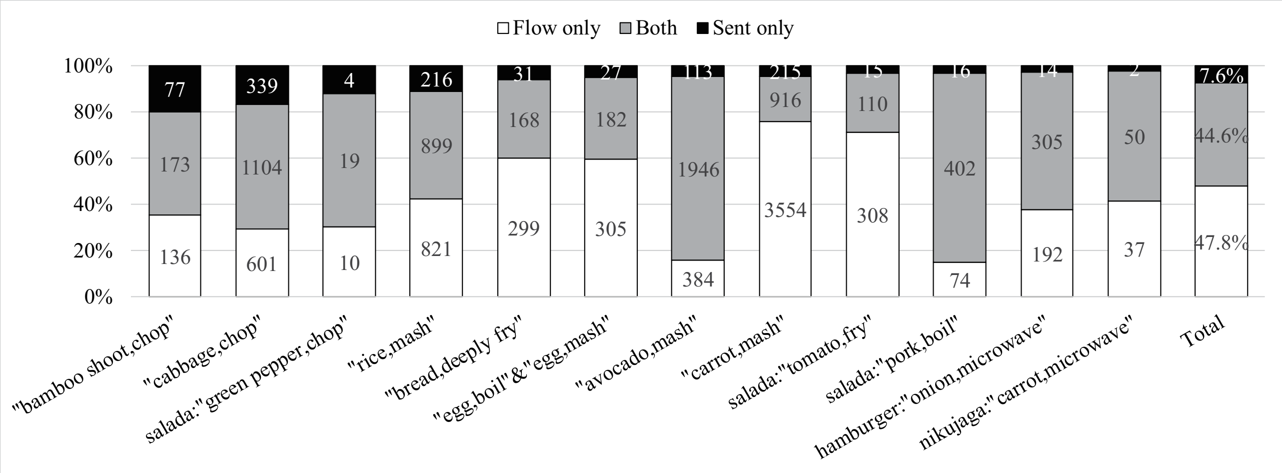

Fig. 3 Numbers and percentages of search results respecting Flow and Sent.Bow comparison.

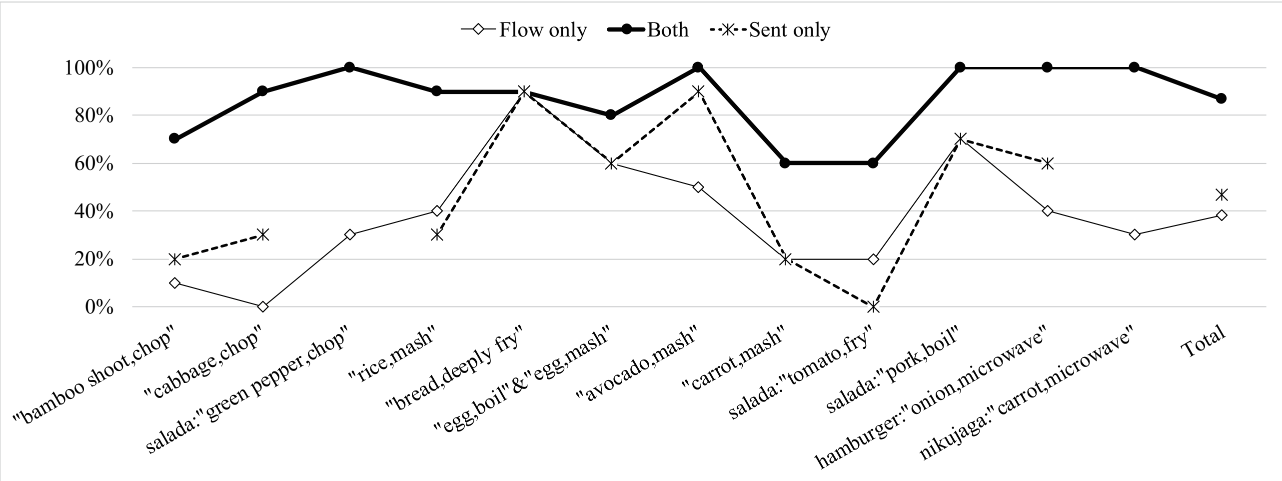

Fig. 4 Precisions of 12 search results respecting Flow and Sent.Bow comparison. The data is omitted from the graph for such queries that the numbers of the search results are under 10.

Web application.

We are also going to apply this method for calorie estimation of food. Calories in food depend on not only their ingredients and amount but also which cooking actions are performed to them during the cooking procedure. The standard tables of food composition in Japan[*12], which is provided by ministry of education, culture, sports, science and technology, Japan and is used for professional dieticians to calculate a food calorie, gives calories of combination of ingredients and description such as “Pork, large type breed, picnic shoulder, lean and fat, raw,” “Carrot, regular (European type), root without skin, deep-fried carrot,” “Potatoes, dehydrated mashed potato,” and so on. We consider the proposed method is applicable to calculate more precise calorie of a food, to find a recipe of lower calorie using the same ingrediens, and so on.

∗12 http://www.mext.go.jp/a_menu/syokuhinseibun/1365297.htm

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◇ References ◇

[Ahn 11] Ahn, Y.-Y., Ahnert, S. E., Bagrow, J. P., and Barabási, A.-L.: Flavor Network and the Principles of Food Pairing, *Scientific Reports*, Vol. 1, No. 196 (2011)

[Badra 09] Badra, F., Cojan, J., Cordier, A., Lieber, J., Meilender, T., Mille, A., Molli, P., Nauer, E., Napoli, A., Skaf-Molli, H., and Toussaint, Y.: Knowledge Acquisition and Discovery for the Textual Case-Based Cooking System WikiTaaable, in *Computer Cooking Contest Workshop at the 8th International Conference on Case-Based Reasoning (ICCBR'09)* (2009)

[Ding 13] Ding, X., Dou, Z., Qin, B., Liu, T., and Wen, J.: Improving Web Search Ranking by Incorporating Structured Annotation of Queries, in *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pp. 468–478 (2013)

[Druck 12] Druck, G. and Pang, B.: Spice it up? Mining Refinements to Online Instructions from User Generated Content, in *Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 545–553 (2012)

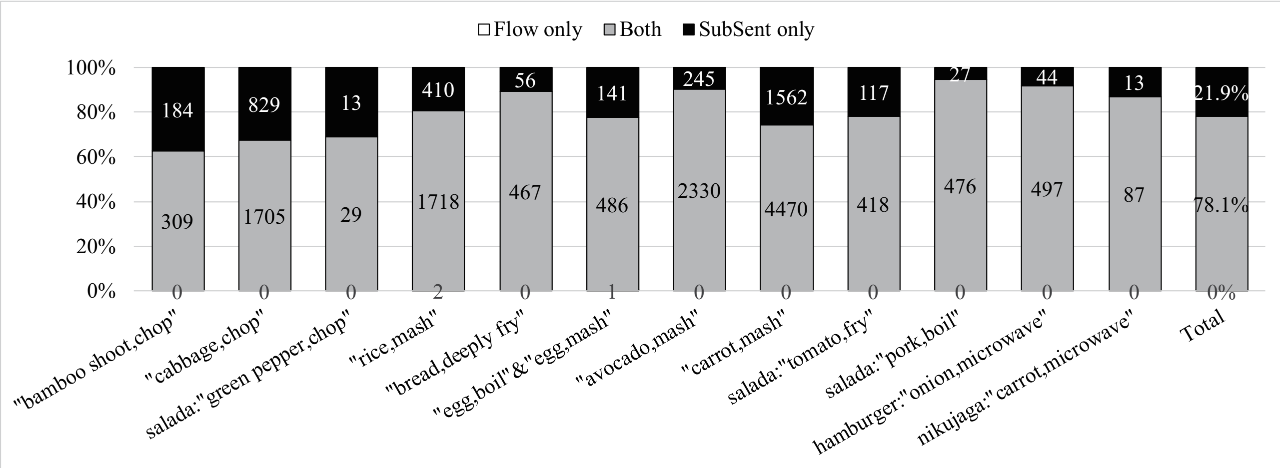

Fig. 5　Numbers and percentages of search results respecting Flow and SubSent.Bow comparison.

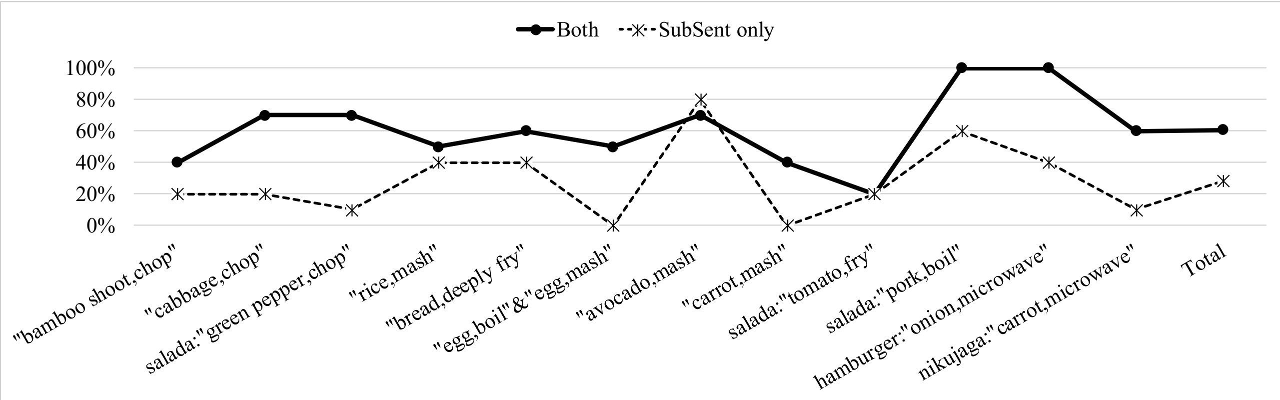

Fig. 6　Precisions of 12 search results respecting Flow and SubSent.Bow comparison.

[Hammond 86]　Hammond, K.: CHEF: A Model of Case-based Planning, in *Proceedings of AAAI-86*, pp. 267–271 (1986)

[Harashima 16]　Harashima, J., Ariga, M., Murata, K., and Ioki, M.: A Large-scale Recipe and Meal Data Collection as Infrastructure for Food Research, in *Proceedings of the 10th International Conference on Language Resources and Evaluation (LREC 2016)* (2016)

[Ihle 09]　Ihle, N., Newo, R., Hanft, A., Bach, K., and Reichle, M.: CookIIS - A Case-based Recipe Advisor, in *Computer Cooking Contest Workshop at the 8th International Conference on Case-Based Reasoning, ICCBR'09*, pp. 269–278 (2009)

[Jermsurawong 15]　Jermsurawong, J. and Habash, N.: Predicting the Structure of Cooking Recipes, in *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pp. 781–786 (2015)

[Kiddon 15]　Kiddon, C., Ponnuraj, G. T., Zettlemoyer, L., and Choi, Y.: Mise en Place: Unsupervised Interpretation of Instructional Recipes, in *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pp. 982–992 (2015)

[Kuo 12]　Kuo, F.-F., Li, C.-T., Shan, M.-K., and Lee, S.-Y.: Intelligent Menu Planning: Recommending Set of Recipes by Ingredients, in *Proceedings of the ACM Multimedia 2012 Workshop on Multimedia for Cooking and Eating Activities (CEA '12)*, pp. 1–6 (2012)

[Maeta 15]　Maeta, H., Sasada, T., and Mori, S.: A Framework for Procedural Text Understanding, in *Proceedings of the 14th International Conference on Parsing Technologies* (2015)

[Mori 14]　Mori, S., Maeta, H., Yamakata, Y., and Sasada, T.: Flow Graph Corpus from Recipe Texts, in *Proceedings of the 9th International Conference on Language Resources and Evaluation (LREC'14)* (2014)

[Tsukuda 10]　Tsukuda, K., Yamamoto, T., Nakamura, S., and Tanaka, K.: Plus One or Minus One: A Method to Browse from an Object to Another Object by Adding or Deleting an Element, in *Database and Expert Systems Applications, 21st International Conference (DEXA) Proceedings Part II*, pp. 258–266 (2010)

[Ueda 14]　Ueda, M., Asanuma, S., Miyawaki, Y., and Nakajima, S.: Recipe Recommendation Method by Considering the User's Preference and Ingredient Quantity of Target Recipe, in *International MultiConference of Engineers and Computer Scientists 2014*, pp. 519–523 (2014)

[Varshney 13]　Varshney, K. R., Varshney, L. R., Wang, J., and Myers, D.: Flavor Pairing in Medieval European Cuisine: A Study in Cooking with Dirty Data, *CoRR*, Vol. abs/1307.7982 (2013)

[Wang 08]　Wang, L., Li, Q., Li, N., Dong, G., and Yang, Y.: Substructure Similarity Measurement in Chinese Recipes, in *Proceedings of the 17th International Conference on World Wide Web (WWW '08)*, pp. 979–988 (2008)

[Xie 10]　Xie, H., Yu, L., and Li, Q.: A Hybrid Semantic Item Model for Recipe Search by Example, in *2010 IEEE International Symposium on Multimedia (ISM)*, pp. 254–259 (2010)

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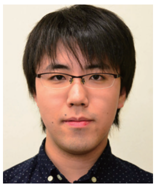

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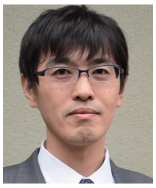

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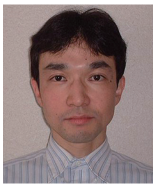

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