Cookpad Parsed Corpus: Linguistic Annotations of Japanese Recipes

Jun Harashima and Makoto Hiramatsu
Cookpad Inc.
{jun-harashima, himkt}@cookpad.com

Abstract

It has become increasingly common for people to share cooking recipes on the Internet. Along with the increase in the number of shared recipes, there have been corresponding increases in recipe-related studies and datasets. However, there are still few datasets that provide linguistic annotations for the recipe-related studies even though such annotations should form the basis of the studies. This paper introduces a novel recipe-related dataset, named Cookpad Parsed Corpus, which contains linguistic annotations for Japanese recipes. We randomly extracted 500 recipes from the largest recipe-related dataset, the Cookpad Recipe Dataset, and annotated 4,738 sentences in the recipes with morphemes, named entities, and dependency relations. This paper also reports benchmark results on our corpus for Japanese morphological analysis, named entity recognition, and dependency parsing. We show that there is still room for improvement in the analyses of recipes.

1 Introduction

Today, a great number of cooking recipes are available on the Internet. Many people upload their recipes to recipe-sharing services such as Cookpad and Yummly, with Cookpad having over six million recipes and Yummly over two million recipes, to date.

As the number of shared online recipes increases, many recipe-related datasets have been published (Salvador et al., 2017; Yagcioglu et al., 2018; Chandu et al., 2019; Lin et al., 2020). These datasets have successfully contributed their content to a variety of recipe-related studies about recipe understanding, recipe search, recipe generation, and so on.

Nevertheless, there are still few datasets that contain linguistic annotations for cooking recipes. Most of the recipe studies rely on linguistic analyses, like those focusing on other text such as newspaper articles. Since linguistic annotations play an important role in fundamental analyses, they are also deserving of more attention in this field.

In this paper, we introduce our Cookpad Parsed Corpus, which is a novel dataset of Japanese recipes. We extract 500 recipes randomly from the Cookpad Recipe Dataset (Harashima et al., 2016), currently the largest recipe dataset, and annotate 4,738 sentences in the recipes with the most fundamental linguistic information: morphemes, named entities, and dependency relations.

We also report benchmark results of the corpus for morphological analysis (MA), named entity recognition (NER), and dependency parsing (DP) for Japanese, and investigate whether tools or methods which have been commonly used for these analyses perform sufficiently for cooking recipes.

2 Related Works

Table 1 summarizes existing recipe-related datasets and our corpus. As shown in the table, each resource has recipes with their own content, such as graph representations and cooking images of the recipes. This work is licensed under a Creative Commons Attribution 4.0 International License. Licence details: http://creativecommons.org/licenses/by/4.0/.

Both authors equally contributed to this work.
content has successfully promoted a variety of recipe-related studies about recipe understanding, recipe search, recipe generation, and so on.

Our corpus differs from these efforts in that it contains linguistic annotations of cooking recipes. In other words, the existing datasets have not taken account of the information, except for the Flow Graph Corpus (Mori et al., 2014) and English Recipe Flow Graph Corpus (Yamakata et al., 2020), which contain a few limited linguistic annotations such as named entities. By contrast, our corpus contains a variety of linguistic annotations such as morphemes, named entities, and dependency relations.

Table 2 summarizes existing Japanese parsed corpora and our corpus. There are several parsed corpora which have contributed their linguistic annotations to linguistic analyses such as MA, NER, and DP for Japanese. In particular, the Kyoto University Text Corpus (Kawahara et al., 2002) and NAIST Text Corpus (Iida et al., 2007) have been commonly used for such studies.

One of the biggest differences between these and our work is the target documents for annotations; that is, the other works focus on newspaper articles, dictionary entries, blogs, web documents, books, and magazines, whereas our corpus is the first to focus on cooking recipes.

3 Cookpad Parsed Corpus

In this study, we constructed a novel recipe-related dataset, named Cookpad Parsed Corpus, which contains linguistic annotations of Japanese recipes. We randomly selected 500 recipes from the largest recipe dataset, Cookpad Recipe Dataset (Harashima et al., 2016), which contains approximately 1.7 million Japanese recipes. We then annotated 4,738 sentences (hereafter called the target sentences) in the 500 recipes with morphemes, named entities, and dependency relations.

Figure 1 shows linguistic annotations for an example sentence in our corpus. The lines starting with # represent the IDs of the step in the recipe and the sentence in the step, respectively, while EOS represents the end of the sentence. The format of our corpus is based on the Kyoto University’s corpora (Kawahara et al., 2002; Hashimoto et al., 2011; Hangyo et al., 2012) and output of CaboCha, which is one of the most popular dependency parsers for Japanese.

We first annotated the target sentences with morphemes. In Figure 1, the lines starting with a word such as 鮭 (salmon) give its morphological information such as part-of-speech (POS), fine-grained POS, base form, reading, pronunciation, and so on. We followed the IPA dictionary (Asahara and Matsumoto, 2003) to decide boundaries and POS for each morpheme because that resource is most commonly used
Figure 1: Linguistic annotations for an example sentence, 生鮭は一口大に切り塩をふる。 (Cut the raw salmon into bite-size chunks and sprinkle them with salt.), in our corpus.

| Tag | Description |
|-----|-------------|
| Fi  | Food (ingredient) |
| Fe  | Food (part to be eliminated) |
| Fd  | Food (dish) |
| Fa  | Food (attribute) |
| Tg  | Tool (general) |
| Ta  | Tool (attribute) |
| To  | Tool (other) |
| Nd  | Number (duration) |
| Nq  | Number (quantity) |
| No  | Number (other) |
| Af  | Action (food) |
| At  | Action (tool) |
| Ap  | Action (person) |
| Sf  | State (food) |
| St  | State (tool) |
| Sap | State (person’s action) |
| X   | Unclassified named entity |

Table 3: Our named entity tags.

| Type | Description |
|------|-------------|
| 主題 | Topic |
| 補足語 | Complement |
| 項体修飾語 | Adnominal modifier |
| 運用修飾語 | Predicative modifier |
| 送語 | Predicate |
| 独立語 | Independent |
| その他 | Other |

Table 4: Our bunsetsu types.

for Japanese MA. We also determined boundaries and POS for unknown words so that they fit the policies of the dictionary as much as possible. Consequently, 62,146 morphemes were annotated in the target sentences.

We then annotated the 62,146 morphemes with named entity tags. Table 3 shows our defined 17 tags, which are based on the 8 tags in the Flow Graph Corpus. In our corpus, the tags are located at the end of morphological information, as seen in Figure 1. Note that we used the common IOB2 format in NER to represent the inside (I), outside (O), and the beginning (B) of a named entity. For example, we can see from the figure that 生 (raw) is the beginning of the ingredient 生鮭 (raw salmon) because the morpheme is annotated with B-Fi. In this annotation, 22,359 entities were finally obtained from the target sentences.

We annotated a further 26,501 bunsetsus in the target sentences with dependency relations. A bunsetsu is a conventional unit of Japanese that consists of one or more content words (e.g., noun) and zero or more function words (e.g., particle). The example sentence in Figure 1 consists of five bunsetsus: 生鮭は一口大に切り塩をふる。, and the lines starting with * give bunsetsu information. For example, the 0 in the first line starting with * denotes the index of the bunsetsu 生鮭は. The 4 in 4D denotes the index of the bunsetsu 生鮭は, which is the head of 生鮭は, while the D denotes the type of dependency relations, such as D (normal dependency), P (coordination dependency), and A (appositive dependency). Note that the index is set to -1 for the last bunsetsu in each sentence. This is because a dependency basically goes from left to right in Japanese, and thus the last bunsetsu has no head bunsetsu. Finally, we defined the 7 bunsetsu types in Table 4 and annotated all the bunsetsus with the types to clarify their roles in a sentence.

Our corpus enables researchers to use the above linguistic annotations for their studies. It was designed to link with two existing datasets: Cookpad Recipe Dataset and Cookpad Image Dataset (Harashima et al., 2017), which provide a variety of content such as reviews, meals, and images of the same 1.7 million recipes. As described, we extracted our 500 recipes from these recipes. This enables researchers to use not only the linguistic annotations of the 500 recipes in our corpus but also access the variety of content of the recipes in the two datasets for their studies.
Table 5: Benchmark results on our corpus.

|               | Precision | Recall | F1    | Accuracy     |
|---------------|-----------|--------|-------|--------------|
| MeCab         | 88.91     | 88.95  | 88.93 |              |
| MeCab w/ DA   | 91.12     | 91.04  | 91.08 |              |
| CaboCha       |           |        |       | 92.21        |
| CaboCha w/ DA |           |        |       | 94.08        |

(a) MA.

|               | Precision | Recall | F1    |
|---------------|-----------|--------|-------|
| Sasada et al. (2015) | 88.30 | 74.85 | 82.77 |
| Lample et al. (2016)   | 91.41 | 88.17 | 87.50 |

(c) DP.

|               | Accuracy | Precision | Recall | F1    |
|---------------|----------|-----------|--------|-------|
| Sasada et al. (2015) | 88.30 | 74.85 | 82.77 | 78.30 |
| Lample et al. (2016)   | 91.41 | 88.17 | 87.50 | 87.67 |

(b) NER.

4 Experiments

Finally, we present benchmark results of our corpus for fundamental linguistic analyses in Japanese. In our experiments, we randomly divided the corpus into 400 recipes (3,783 sentences) for a training set, 50 recipes (472 sentences) for a validation set, and 50 recipes (483 sentences) for a test set. Then, we trained, tuned, and tested popular tools or methods for Japanese MA, NER, and DP using these recipes.

Table 5(a) shows the results for MA. We measured the performance of MeCab, the de facto standard morphological analyzer for Japanese, with and without performing domain adaptation (DA) of the tool for cooking recipes using our training set. The precision, recall, and F1 in the table were calculated based on the correct morphemes which the analyzer could recognize in our test set. From the table, we can see that all the metrics were approximately 91% even if we performed DA. This indicates that MA for informal cooking recipes is still an unsolved problem, compared to that for formal newspaper articles on which the tool has already achieved metrics of over 98% in Kudo et al. (2004).

The results for NER are given in Table 5(b). As there is no existing named entity recognizer that uses our named entity tags, two recognizers proposed in Sasada et al. (2015) and Lample et al. (2016), which are popular in recipe and general domains, respectively, were trained and evaluated using our training and test sets. The metrics in the table were calculated in the same way in the CoNLL-2003 shared task (Sang and Meulder, 2003). From the table, it is clear that there is still room for improvement in NER for cooking recipes. Most of the errors in our experiment were caused by domain-specific unknown words. Thus, a domain-specific lexicon such as cooking ontology (Nanba et al., 2014) may play an important role in reducing such errors.

Table 5(c) shows the results for DP. For this experiment, we used CaboCha, also mentioned in the previous section. The accuracy in the table was the percentage of the correct dependencies which the parser could recognize in our test set. Interestingly, the accuracy of 92-94% of the parser on our corpus was higher than the 90% for the Kyoto University Text Corpus, reported in Kudo and Matsumoto (2002). In other words, DP for informal cooking recipes might be slightly easier than for formal newspaper articles. This is probably because sentences in cooking recipes are relatively short, compared to those in newspaper articles. Having said that, we found that over 20% of the sentences in our test set had at least one parsing error even when we performed DA with the parser. This suggests that DP for cooking recipes also remains an unsolved problem.

5 Conclusion

This paper introduced the Cookpad Parsed Corpus, which contains linguistic annotations of Japanese recipes. The corpus was composed of 500 recipes which were extracted from the Cookpad Recipe Dataset. A total of 4,738 sentences in the recipes were annotated with morphemes, named entities, and dependency relations. Benchmark results on our corpus for Japanese MA, NER, and DP were reported, and showed that there is still room for improvement in these analyses of cooking recipes. We believe the linguistic annotations will form a basic infrastructure not only for the improvement of the fundamental analyses, but also for the variety of recipe-related studies based on the analyses. The dataset can be obtained by sending an e-mail request to the authors. In future work, we plan to enrich our corpus with further linguistic annotations such as predicate-argument structures and co-references.
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