Correction of Errors in a Modality Corpus Used for Machine Translation by Using Machine-learning Method

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Abstract

We performed corpus correction on a modality corpus for machine translation by using such machine-learning methods as the maximum-entropy method. We thus constructed a high-quality modality corpus based on corpus correction. We compared several kinds of methods for corpus correction in our experiments and developed a good method for corpus correction.

1 Introduction

In recent years, various types of tagged corpora have been constructed and much research using tagged corpora has been performed. However, tagged corpora include errors, which impede the progress of research. Therefore, the correction of errors in corpora is an important research issue.

We have researched error correction in corpora by using the modality corpus we are currently constructing. This modality corpus consists of supervised learning data used for research on translating Japanese tense, aspect, and modality into English.

Figure 1: Part of the modality corpus

. kono kodomo wa aa ieba kou iu kara koniku-rashii
This child always talks back to me, and this <v>is</v> why I <v>j>hate</v> him.

d kare ga aa okubyou da to wa omowana-katta
I <v>did not think</v> he was so timid.

c aa isogashikute wa yasumu hima monai hazu da
Such a busy man as he <v>cannot</v> have<v>/v> any spare time.

1 There is no previous paper on error correction in corpora. In terms of error detection in corpora, there has been research using boosting or anomaly detection (Abney et al., 1999; Eskin, 2000).

2 This paper is the English translation of the paper (Murata et al., 2001b). We also performed corpus correction in a morphological corpus (Murata et al., 2000).
2 Modality Corpus for Machine Translation

In this section, we describe the modality corpus. A part of it is shown in Figure 1. It is composed of a Japanese-English bilingual corpus, and each English sentence can include the following two types of tags.

- The English main verb phrase is tagged with $<v>$.
- The English verb phrase corresponding to the Japanese main verb phrase is tagged with $<vj>$.

The symbols at the beginning of each Japanese sentence, such as “c” and “d”, indicate a category of tense, aspect, and modality for the sentence. (For example, “c” and “d” indicate “can” and “past tense”, respectively. The first symbol in Figure 1 is “,”. This symbol is used when $<vj>$ is used, such that the left part indicates the category of the verb phrase tagged with $<v>$ and the right part indicates the category of the verb phrase tagged with $<vj>$). In this corpus, the number of examples of present tense is large, so the symbol for present tense is null expression (i.e., “”). $<vj>$ is tagged when the verb phrase with $<v>$ does not correspond with the Japanese main verb.

We use the following 34 categories for tense, aspect, and modality. These categories are determined by the surface expressions of the English verb phrases.

1. all combinations of \{present tense, past tense\}, \{progressive, not-progressive\}, and \{perfect, not-perfect\} (8 categories)
2. imperative mood (1 category)
3. auxiliary verbs \{\{present tense, past tense\} of “be able to”, \{present tense, past tense\} of “be going to”, “can”, “could”, \{present tense, past tense\} of “have to”, “had better”, “may”, “might”, “must”, “need”, “ought”, “shall”, “should”, “used to”, “will”, “would”\} (19 categories)
4. noun phrases (one category)
5. participial construction (one category)
6. verb ellipsis (one category)
7. interjection or greeting sentences (one category)
8. the case when a Japanese main verb phrase cannot correspond to an English verb phrase (one category)
9. the case when tagging cannot be performed (one category)

These categories of tense, aspect, and modality are defined on the basis of the surface expressions of the English sentences. So, if we can estimate the correct category from a Japanese sentence, we should be able to translate the Japanese tense, aspect, and modality into English. Therefore, in researching the translation of modality expressions based on the machine-learning method, only the tags indicating the categories of tense, aspect, and modality and the Japanese sentences are used.

We placed an order with an outside company to construct the modality corpus according to the above conditions. We used about 40,000 example sentences from the Kodansha Japanese-English dictionary \[(Shimizu and Narita, 1976)\] as a bilingual corpus. The outside company performed the tagging of $<v>$ and the corresponding categories of modality by hand. Inspection work was performed more than twice, until the outside company considered no errors at all to exist in the corpus.
3 Method of Corpus Correction

In this section, we describe the method of correcting errors in the modality corpus constructed by hand, as described in the previous section. The method is to calculate the probabilities of tags, which are objects for error correction in a corpus, and then perform corpus correction by using those probabilities. In this paper, we only consider tags for modality categories, not “<v>” and “<vj>” tags.

We tested two kinds of methods for calculating the probability of each tag: the maximum-entropy method, and the decision-list method.

- Method based on the maximum-entropy method (Ristad, 1997; Ristad, 1998)

In this method, the distribution of probabilities \( p(a, b) \) is calculated for the case when Equation (1) is satisfied and Equation (2) is maximized, and the desired probabilities \( p(a|b) \) are then calculated by using the distribution of probabilities \( p(a, b) \):

\[
\sum_{a \in A, b \in B} p(a, b)g_j(a, b) = \sum_{a \in A, b \in B} \tilde{p}(a, b)g_j(a, b) \quad (1)
\]

\[
H(p) = - \sum_{a \in A, b \in B} p(a, b) \log(p(a, b)). \quad (2)
\]

where \( A, B, \) and \( F \) are sets of categories, contexts, and features \( f_j(\in F, 1 \leq j \leq k) \), respectively; \( g_j(a, b) \) is a function defined as 1 when context \( b \) has feature \( f_j \) and the category is \( a \), or defined as 0 otherwise; and \( \tilde{p}(a, b) \) is the occurrence rate of \( (a, b) \) in the training data.

In general, the distribution of \( \tilde{p}(a, b) \) is very sparse. We cannot use it directly, so we must estimate the true distribution of \( p(a, b) \) from the distribution of \( \tilde{p}(a, b) \). We assume that the estimated values of the frequency of each pair of category and feature as calculated from \( \tilde{p}(a, b) \) are the same as those from \( p(a, b) \) (This corresponds to Equation (1)). These estimated values are not so sparse. We can thus use the above assumption for calculating \( p(a, b) \). Furthermore, we maximize the entropy of the distribution of \( \tilde{p}(a, b) \) to obtain one solution of \( p(a, b) \), because only using Equation (4) produces many solutions for \( \tilde{p}(a, b) \). Maximizing the entropy has the effect of making the distribution more uniform and is known to be a good solution for data sparseness problems.

- Method based on the decision-list method (Yarowsky, 1994)

In this method, the probability of each category is calculated by using one of features \( f_j(\in F, 1 \leq j \leq k) \). The probability that produces category \( a \) in context \( b \) is given by the following equation:

\[
p(a|b) = p(a|f_{max}), \quad (3)
\]

such that \( f_{max} \) is defined by

\[
f_{max} = \arg \max_{f_j \in F} \max_{a_i \in A} \tilde{p}(a_i|f_j), \quad (4)
\]

where \( \tilde{p}(a_i|f_j) \) is the occurrence rate of category \( a_i \) when the context has feature \( f_j \).

In this paper, we used the following items as features, which are the context when the probabilities are calculated. \( (26 (= 5 + 10 + 10 + 1) \) features appear in each English sentence.)
• The strings of 1-gram to 5-gram just to the left of \textless v\textgreater in the sentence.
  (e.g.) I \textless v\textgreater did not think\textless /v\textgreater he was so timid.

• The strings of 1-gram to 10-gram just to the right of \textless v\textgreater.
  (e.g.) I \textless v\textgreater did not think\textless /v\textgreater he was so timid.

• The strings of 1-gram to 10-gram just to the left of \textless /v\textgreater.
  (e.g.) I \textless v\textgreater did not think\textless /v\textgreater he was so timid.

• The 1-gram string at the end of the sentence.
  (e.g.) I \textless v\textgreater did not think\textless /v\textgreater he was so timid.

When the verb phrase was divided into two parts, as in an interrogative sentence, the above extraction of features was performed after eliminating the words between the first \textless /v\textgreater and the second \textless v\textgreater.

Because the corpus used in this paper was designed for estimating the modality of the English sentence from the Japanese sentence, one may think that we should extract the features from the Japanese sentence. It is true if we want to infer English modalities from Japanese sentences. What we want to do is, however, to correct English modality tags. Thus we should use all the information available. Since the category of the modality expression of the English sentence is tagged and the verb phrase of the English sentence is examined for construction of the corpus by hand, it is reasonable to use the English verb phrase in corpus correction based on the machine-learning method.

Next, we describe the method of judging whether each tag in the corpus is incorrect or not. We first calculate the probabilities of the category of the tag, and of the other categories. We judge that the tag is correct when its category has the highest probability and incorrect when one of the other categories has the highest probability. Next, we correct the tag if it is judged to be incorrect. This correction is performed by changing the tag to the tag of the category with the highest probability. (This correction is confirmed by annotators in actuality.)

Corpus correction should be confirmed by human beings. Therefore it is very time consuming. However, when the probabilities of each tag can be calculated, we can define the confidence value of the corpus correction, as described below. It is thus more convenient to sort the error candidates in the corpus by confidence value and begin by correcting the errors for which the confidence value is higher.

We tested the following two types of methods for determining the confidence value for corpus correction.

• **Method 1** — the probability of the category with the highest probability is used as the confidence value for corpus correction.

• **Method 2** — the non-probability of the tag originally defined is used as the confidence value for corpus correction.

In this paper, the non-probability is defined as the value obtained by subtracting the probability from 1.

We finally explain the methods to use data for calculating probabilities. There are two kinds of methods for calculating the probabilities by using the machine-learning method:

• calculation of probabilities for the closed data, and

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\[4\] This action of corpus correction is exactly equivalent to redefining the tag in the corpus by using a machine-learning method and re-tagging the newly defined tag.
• calculation of probabilities for the open data.

The first method calculates probabilities by using all the tags in the corpora including the tag which is judged currently. The second method does not use the tag which is judged currently. In this paper, 10-fold cross validation was used for calculating probabilities for the open data. 

4 Experiments on Corpus Correction

We carried out experiments on corpus correction by using the methods described in the previous section. These experiments were performed after eliminating the sentences given tags indicating that tagging could not be performed. Thus, these experiments were performed for 39,718 modality tags. The results are shown in Tables 1 to 4. “random 300” indicates the precisions for 300 tags extracted randomly from among the tags corrected by our system. “top X” indicates the precisions for the top X tags sorted by Method 1 or Method 2. “Precision for detection” indicates the percentage of tags for which detection of an error succeeded in causing the tag to be corrected by our system, while “Precision for correction” indicates the percentage of tags for which correction of an error succeeded in causing the tag to be corrected by our system.

We came to the following conclusions based on the experimental results.

• Throughout all the experiments, the precisions for detection and correction were almost the same. Thus, we found that it is more convenient to perform both correction and detection, rather than only detection.

From the viewpoint of manual modification, when we modify tags by hand, it is also more convenient for the system to produce a candidate category that is tagged to the corpus after corpus correction. This is because we can find how the original tag was incorrect and how we should change it to the new corrected tag. When only detection is performed, in other words, a candidate category is not presented, an annotator may not know why the tag is incorrect.

• In general, the maximum-entropy method produced higher precision than the decision-list method. However, when the closed data was used to calculate the probabilities, the precisions of the top items were almost the same for the two methods.

• In terms of the precisions of top items, using the closed data to calculate the probabilities was better than using the open data. However, in terms of the total number of extracted items, using the open data was better.

• In terms of sorting by Method 1 or Method 2, Method 1 generally produced higher precisions for the top items than Method 2.

• In terms of comparing “random 300” and “top X”, “top X” produced much higher precisions for the top items than “random 300”. We thus found that sorting by confidence values of corpus correction is very important.

Based on the above results, we think

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5When the probabilities are calculated using open data in the decision-list method, the probability of the category of the original tag is apt to be 0, or the probability of the category of the tag defined after corpus correction is apt to be 1, because the calculation is performed by not using the original tag. Thus when there are many such tags, many of them have the same probability and sorting by probabilities becomes difficult. In this case, we sort the tags by arranging those whose probability is calculated from the features which have many tags in descending order of confidence value for corpus correction.
Table 1: Precision of corpus correction using the maximum-entropy method (The probabilities were calculated using the closed data. 184 candidate errors were extracted.)

|                | Precision for detection | Precision for correction |
|----------------|-------------------------|--------------------------|
|                |                         |                         |
| random 300     |                         |                         |
| Method 1       |                         |                         |
| top 50         | 100% (50/50)            | 100% (50/50)             |
| top 100        | 92% (92/100)            | 92% (92/100)             |
| top 150        | 77% (116/150)           | 77% (116/150)            |
| top 200        | 69% (127/184)           | 68% (126/184)            |
| top 250        |                         |                         |
| top 300        |                         |                         |
| Method 2       |                         |                         |
| top 50         | 88% (44/50)             | 88% (44/50)              |
| top 100        | 81% (81/100)            | 81% (81/100)             |
| top 150        | 74% (112/150)           | 74% (111/150)            |
| top 200        | 69% (127/184)           | 68% (126/184)            |
| top 250        |                         |                         |
| top 300        |                         |                         |

Table 2: Precision of corpus correction using the maximum-entropy method (The probabilities were calculated using the open data. 694 candidate errors were extracted.)

|                | Precision for detection | Precision for correction |
|----------------|-------------------------|--------------------------|
|                |                         |                         |
| random 300     |                         |                         |
| Method 1       |                         |                         |
| top 50         | 88% (44/50)             | 88% (44/50)              |
| top 100        | 88% (88/100)            | 88% (88/100)             |
| top 150        | 80% (121/150)           | 79% (119/150)            |
| top 200        | 68% (136/200)           | 67% (134/200)            |
| top 250        | 60% (151/250)           | 59% (149/250)            |
| top 300        | 53% (160/300)           | 52% (157/300)            |
| Method 2       |                         |                         |
| top 50         | 72% (36/50)             | 72% (36/50)              |
| top 100        | 74% (74/100)            | 71% (71/100)             |
| top 150        | 70% (106/150)           | 68% (102/150)            |
| top 200        | 67% (135/200)           | 65% (131/200)            |
| top 250        | 60% (152/250)           | 58% (147/250)            |
| top 300        | 52% (157/300)           | 50% (152/300)            |
Table 3: Precision of corpus correction using the decision-list method (The probabilities were calculated using the closed data. 383 candidate errors were extracted.)

| Method   | top 50 | top 100 | top 150 | top 200 | top 250 | top 300 |
|----------|--------|---------|---------|---------|---------|---------|
| Method 1 | 100%   | 92%     | 76%     | 62%     | 51%     | 44%     |
|          | (50/50)| (92/100)| (115/150)| (124/200)| (128/250)| (132/300)|
|          | 100%   | 92%     | 74%     | 60%     | 50%     | 43%     |
|          | (50/50)| (92/100)| (112/150)| (121/200)| (125/250)| (129/300)|
| Method 2 | 88%    | 86%     | 71%     | 59%     | 50%     | 43%     |
|          | (44/50)| (86/100)| (107/150)| (118/200)| (126/250)| (129/300)|
|          | 86%    | 84%     | 69%     | 57%     | 49%     | 42%     |
|          | (43/50)| (84/100)| (104/150)| (115/200)| (123/250)| (126/300)|

Table 4: Precision of corpus correction using the decision-list method (the probabilities were calculated using the open data. 694 candidate errors were extracted.)

| Method   | top 50 | top 100 | top 150 | top 200 | top 250 | top 300 |
|----------|--------|---------|---------|---------|---------|---------|
| Method 1 | 56%    | 43%     | 31%     | 26%     | 22%     | 20%     |
|          | (28/50)| (43/100)| (47/150)| (52/200)| (55/250)| (61/300)|
|          | 52%    | 40%     | 29%     | 24%     | 20%     | 19%     |
|          | (26/50)| (40/100)| (44/150)| (48/200)| (51/250)| (57/300)|
| Method 2 | 66%    | 48%     | 44%     | 35%     | 30%     | 26%     |
|          | (33/50)| (48/100)| (66/150)| (71/200)| (77/250)| (80/300)|
|          | 64%    | 46%     | 42%     | 34%     | 29%     | 25%     |
|          | (32/50)| (46/100)| (63/150)| (68/200)| (73/250)| (76/300)|
that the following strategy is a better solution.

1. We first perform high-quality corpus correction by using the probability calculation for the closed data and Method 1.

2. Next, we perform corpus correction for a much larger number of tags by using the probability calculation for the open data, the maximum-entropy method, and Method 1.

5 Conclusion

In this paper, we have described corpus correction using a machine-learning method for a modality corpus for machine translation. We have constructed a high-quality modality corpus by using corpus correction. In the future, we plan to research Japanese-English translation of tense, aspect, and modality by using this corpus.

Our method of corpus correction has the following advantages.

• There is no previous paper on error correction in corpora.

In terms error detection in corpora, there has been research using boosting or anomaly detection ([Abney et al. 1999; Eskin, 2000]). We found that the precisions for detection and correction were almost the same. Therefore, we should perform correction in addition to detection.

• Our method calculates the probability of each tag and can sort the error candidates in the corpus by using these probabilities as confidence values for corpus correction. Thus, we can begin to correct errors for which the confidence value is higher.

• Our method uses the machine-learning method and inherits its original advantages.
  
  – Our method has the same wide applicability as the machine-learning method and can be used to correct a various types of corpora.
  
  – A large amount of human effort is not necessary, and human beings only have to provide appropriate feature sets used in the machine-learning method.

 References

[Abney et al.1999] Steven Abney, Robert E. Schapire, and Yoram Singer. 1999. Boosting applied to tagging and PP attachment. *EMNLP/VLC-99.*

[Eskin2000] Eleazar Eskin. 2000. Detecting errors within a corpus using anomaly detection. *NAACL-2000.*

[Murata et al.1999] Masaki Murata, Qing Ma, Kiyotaka Uchimoto, and Hitoshi Isahara. 1999. An example-based approach to Japanese-to-English translation of tense, aspect, and modality. In *TMI ’99*, pages 66–76.

[Murata et al.2000] Masaki Murata, Masao Utiyama, Kiyotaka Uchimoto, Qing Ma, and Hitoshi Isahara. 2000. Corpus error detection and correction using the decision-list and example-based methods. *Information Processing Society of Japan, WGNL 2000-NL-136*, pages 49–56. (in Japanese).

[Murata et al.2001a] Masaki Murata, Kiyotaka Uchimoto, Qing Ma, and Hitoshi Isahara. 2001a. Using a support-vector machine for Japanese-to-English translation of tense, aspect, and modality. *ACL Workshop, the Data-Driven Machine Translation.* (to appear).

[Murata et al.2001b] Masaki Murata, Masao Utiyama, Kiyotaka Uchimoto, Qing Ma, and Hitoshi Isahara. 2001b. Correction of the modality corpus for machine translation based on machine-learning method. *7th Annual Meeting of the Association for Natural Language Processing.* (in Japanese).
[Ristad1997] Eric Sven Ristad. 1997. Maximum Entropy Modeling for Natural Language. ACL/EACL Tutorial Program, Madrid.

[Ristad1998] Eric Sven Ristad. 1998. Maximum Entropy Modeling Toolkit, Release 1.6 beta. http://www.mnemonic.com/software/memt.

[Shimizu and Narita1976] Mamoru Shimizu and Narimasu Narita, editors. 1976. The KODANSHA Japanese-English Dictionary. Kodansha.

[Yarowsky1994] David Yarowsky. 1994. Decision lists for lexical ambiguity resolution: Application to accent restoration in Spanish and French. In 32th Annual Meeting of the Association of the Computational Linguistics, pages 88–95.