Universal Model for Paraphrasing
— Using Transformation Based on a Defined Criteria —

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Abstract

This paper describes a universal model for paraphrasing that transforms according to defined criteria. We showed that by using different criteria we could construct different kinds of paraphrasing systems including one for answering questions, one for compressing sentences, one for polishing up, and one for transforming written language to spoken language.

1 Introduction

The term “paraphrasing” used in this paper means the process of rewriting sentences without altering the meaning. It includes generating easy sentences from difficult ones, polished sentences from broken or poor ones, or sentences used in spoken language from ones used in written language, which is useful for generating speech from written texts. Moreover, generating concise sentences that have almost the same meaning as their long, tedious original, which is classified under summarization, is also a type of paraphrasing. Paraphrasing is useful for many natural-language processing techniques, and it is important for generating these techniques.

This paper describes a universal model that achieves many kinds of paraphrasing. It transforms sentences according to a predefined criteria. We show that our model can handle many kinds of paraphrases by selecting the most appropriate criteria for each type of paraphrasing. Since this model includes several of criteria for different types of paraphrasing, it can deal with a whole range of paraphrasing types.

2 Paraphrasing model

Figure 1 shows our paraphrasing model. It consists of two modules: a transformation and an evaluation module. A sentence that requires transformation is input into the system. Several potential transformation types are generated in the transformation module and then tested in the evaluation module, where most appropriate type is selected. It is then used for the transformation and the result is output.

- Transformation module
  This module generates the potential transformation types. They are based on hand-written rules, rules automatically detected by machines, or on a combination of both.

- Evaluation module
  This module selects the most appropriate transformation type by using predefined criteria. The criteria needs to be adapted each time according to the particular problem it should handle.

Here are several example criteria used in the evaluation module:

- Similarity
  To establish the similarity between X and Y, we first suppose that all the rewriting rules in the transformation module comply with the restriction that the transformation does not alter the meaning. We then transform X and Y in the transformation module so that they are similar as possible. Then we calculate their similarity correctly even if X and Y expressed the same meanings differently.
• **Length**
  To compress a sentence without changing the meaning, similarly to the sentence-compression process, which is classified under summarization, we again suppose that all the rewriting rules in the transformation module comply with the restriction that transformation does not alter the meaning. Here, we use the length of the sentence as the main criterion of transformation. We can compress a sentence by repeatedly transforming input sentences to decrease their lengths.

• **Frequency (or probability of occurrence)**
  To polish poor or unconnected sentences also all the rewriting rules in the transformation module have to comply with the restriction that transformation does not alter the meaning. We transform sentences that require polishing according to how frequently part of these sentences appear in the corpora, so they can be transformed into more sophisticated ones. We can explain this by using an easier example: if the input data include the word “summarisation” and the transformation module has a function that changes “summarisation” to “summarization,” we count how often both “summarisation” and “summarization” have so far appeared by using Penn Treebank or another corpus. When the frequency of “summarization” exceeds that of “summarisation,” we change “summarisation” in the input data to “summarization.”

Furthermore, we can use several types of corpora for measuring the frequency or calculating the probability, and they have different results. For example, when input data in written language and corpora comprising of spoken language is used, the input data is converted into spoken language. Thus, if we have input data that include “is not” and the transformation module has a function that changes “is not” to “isn’t,” since “isn’t” occurs more frequently than “is not” in the spoken language corpus, “is not” is changed to “isn’t.”

Now, suppose that the input data are sentences that have difficult expressions such as those used in legal documents. When we use a set of easy sentences for the corpora to measure their frequency, the difficult sentences are transformed into easy ones. Or, suppose that the input data is a novel written by an unknown writer and a set of materials written by Shakespeare is used for the corpora that measures the frequency. In this case, a new novel in Shakespearean style would be output.

• **Judging the grammatical validity of a sentence**
  Measuring the frequency can be used to polish sentences; therefore, it can also be used to judge whether a sentence is grammatical or not. But when the criteria is too restricting for establishing the grammatical validity, we can instead use only one of the following:
  
  - The expressions used in the transformed version should occur at least once in the corpora. (This measure is often used in spell-check systems (Kukich, 1992).)
  - The probability of occurrence in the corpora should exceed a certain threshold.
  - The probability of occurrence in the corpora should be higher than that when the surroundings are not used for calculating the probabilities.

The criteria we described here are more similar to conditions, and would be most effective when combined with other criteria. We should use these criteria additionally when other criteria cannot guarantee the grammatical validation of a sentence in a transformation.

• **Judging the equivalence in meaning of a sentence before and after transformation**
  When we do not know whether the transformation in the transformation module comply with the restriction that the transformation should not alter the meaning of a sentence, this criteria is required. However, we doubt that equivalence in meaning can be judged at all.

For ad hoc solutions we can apply the following two methods, either separately or simultaneously:

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1 Probabilities of occurrence in corpora have been used in many studies on spelling-error correction and generation (Kukich, 1992, Brown et al., 1993, Ratnam and Karkhi, 2000).

2 Moreover, our model can handle machine translation (Brown et al., 1993) by applying translation rules in the transformation module and using corpora written in the target language for calculating the probabilities.
Usually, when a Japanese person hears that an American lives in New York, he or she thinks that the American lives in New York City. This is a common mistake, however. New York City takes up only a very small area of southern New York State. It takes about eight hours to drive from New York City to Niagara Falls, which is also in New York State. The majority of the state consists of mountains, forests, fields, rivers, lakes, and swamps. The people who live in these central and northern areas of the state usually live in small towns. Farming is the most common occupation among these New York State residents, and corn is the most common crop grown by them.

- We check the transformation rules by hand and only use those that satisfy the meaning-equivalence criteria. And/or, we list the cases when the rules satisfy the meaning-equivalence by hand and the ones that do not, and then judge the meaning-equivalence by using that particular data.

- We extract only those rules that reliably satisfy the meaning-equivalence when they are extracted automatically. And/or, we use a machine that learns the conditions when the rules satisfy the meaning-equivalence are also learned automatically when rules are extracted automatically.

This item is more similar to a condition than a criteria, as in the previous item. It is used in addition to other measures.

We can imagine other measures than the ones we described.

In the following sections, we will demonstrate what kinds of criteria we applied for transformation in our model by using concrete examples from our research.

3 The case of a QA system

Our question-answering system takes the following procedures:

1. The system extracts sentences, including the answer of the question sentence, from sentences in the database.
2. The system rewrites the extracted sentences and the question sentence so that they are as similar as possible.
3. The system compares the rewritten sentences from the database to the rewritten question sentence. It then outputs the phrase in the rewritten sentence from the database that corresponds to the interrogative pronoun in the rewritten question sentence as the answer.

For example, when we are given the data (Kyokai, 1985) shown in Table 1, we are asked the question of “What is the most general occupation among the residents of central and northern New York State?” Our system transforms the question sentence into a declarative sentence and the interrogative pronoun is changed to X. The sentence most similar to this question sentence is extracted, and the system takes the state shown in the first line of Table 2. We suppose that our system applies the transformation rule shown in Table 3. The question sentence and the extracted sentences are rewritten to increase the similarity between them. Finally, as shown in the table, the similarity reaches a maximum level of 219.5 and cannot be increased. At this stage, the system accurate question-answering results because the system detects answers when the transformed question sentence and the transformed data sentence are very similar.

Our actual system is in Japanese and the example sentence in this paper is the English translation of the Japanese sentence.

| X is Y | ⇔ | Y is X |
| --- | --- | --- |
| general | ⇔ | common |
| these X residents | ⇔ | these residents of X |
| X | ⇔ | X |

Table 3: transformation rule used in the transformation module
Table 2: Examples of the QA system

| Sim. | quest. | Sentences |
|------|--------|-----------|
| 32.1 |        | The most general occupation among the residents of central and northern New York State is X. |
| 32.1 | data   | Farming is the most common occupation among these New York State residents, and corn is the most common crop grown by them. |
| 103.1| data   | Farming is the most general occupation among these New York State residents, and corn is the most common crop grown by them. |
| 82.5 | data   | Farming is the most common occupation among these residents of New York State, and corn is the most common crop grown by them. |
| 186.5| data   | Farming is the most general occupation among these residents of New York State, and corn is the most common crop grown by them. |
| ...  | ...    | ...       |
| 219.5| quest. | X is the most general occupation among the residents of central and northern New York State. |
| 219.5| data   | Farming is the most general occupation among these residents of New York State |
| Ans. |        | = Farming |
| Sup. |        | = Farming is the most general occupation among these residents of New York State |

compares the sentence from the database and the question sentence and detects “Farming” easily by extracting the phrases in the sentence from the database that correspond to X.

Our QA system paraphrases by using similarity as a criterion. Because the system paraphrases sentences to increase their similarity, it facilitates comparing the question sentence and the data sentence. Here, we showed the QA system as an example. The similarity criterion can also be used for most cases of calculating similarity. For example, a high-level information retrieval system could determine the similarity of a query and a retrieval document after they are rewritten to ensure their similarity is the highest possible.

4 The case of a sentence compression system

Recently, many studies on summarization have been conducted. We also performed sentence compression (Knight and Marcu, 2000), which is classified under summarization.

We researched automatic extraction of rewriting rules from two different dictionaries. Here is a brief explanation of our research. Two Japanese dictionaries gave the definitions shown in Figure 3 for the word abekobe meaning “reverse”. We expected to extract the pairs of expressions having the same meaning by comparing the two definitions, since they both defined the same word and thus had the same meaning. We compared the two by using the unix command “diff” and obtain the results shown in the figure. From the results, we determined that nodo-no “etc.” and “,” were interchangeable, as well as sakasama-ni irekawatte “be changed upside-down” and hikkuri-kaet “be overturned”. We actually obtained 67,632 rewriting rules by using this method. However, they also included many incorrect ones. So we automatically selected rewriting rules that appear more than once in the comparison, because rewriting rules that appear twice or more in the comparison are more accurate.

In our actual experiments, we used probabilistic equations to detect rules. We cannot explain this method in detail in this paper. But the results would

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8 In an anaphora resolution (Murata and Nagao, 1998), the system cannot resolve the anaphora when the identity or inclusion-relationship of “hole” expressed by “a hole which is at the base of a huge cedar tree nearby” and “the hole at the base of the cedar tree” cannot be judged. But when we rewrite them based on the similarity criterion and obtain “a hole at the base of a huge cedar tree nearby” and “the hole at the base of the cedar tree,” the system understands that the former expression includes the latter one (that the two trees, “a huge cedar tree nearby” and “the cedar tree,” are the same is determined easily because the former “tree” only has additional adjectives), and that the latter one refers to the former one.

9 In our actual experiments, we used probabilistic equations to detect rules. We cannot explain this method in detail in this paper. But the results would
Definition of “reverse” in Dictionary A:

junjo, ichi nado -no kankei -ga sakasama-ni irekawa-teiru (order) (,) (location) (etc.) of (relation) nom (upside-down) (change places) (-ing)
(The relationship of the order, location and so on is changed upside-down.)

Definition of “reverse” in Dictionary B:

junjo, ichi, kankei -ga hikkuri-kaet -teiru (order) (,) (location) (,) (relation) nom (be overturned) (-ing)
(The relationship of the order and location is overturned.)

Results of comparing the two definitions

junjo, ichi nado -no kankei -ga sakasama-ni irekawa-teiru (etc.) (of) nom (upside-down) (be changed) hikkuri-kaet (be overturned)

Figure 2: Example of extracting rules for paraphrasing

rules was 775. The research in this section uses these 775 rules as the rules in the transformation module.

Here we considered summarizing newspaper articles and used the following criteria in the evaluation module.

- The transformed sentence should be shorter as possible.
- The expressions in the transformed sentence should appear at least once in the corpora, which contained two-years’ worth of newspaper articles, to verify the grammatical validity of a sentence.

Strictly speaking, we used the following procedures.

1. The system analyzed an input sentence morphologically by using the Japanese morphological analyzer JUMAN [Kurohashi and Nagao, 1998] and divided it into a string of morphemes.

2. The system performed the following procedures for each morpheme from left to right.

   (a) When the string of morphemes $S$, whose first morpheme is the current one (including no morphemes, e.g., “”) matched the $A_i$ string from the transformation rule $R_i$ ($A_i \Rightarrow B_i$), the $B_i$ string was extracted as the candidate of the transformed expression. We referred to the string of the $k$-gram morphemes just before $S$ as $S_1$, and to the one just after as $S_2$.

   (b) The system counted the number of the strings reduced when string $A_i$ was changed to $B_i$ against each $B_i$. We referred to the $i$ when the value was the highest as $m$.

   (c) The system counted the frequency of the string of $S_1 m B_m S_2 m$ in the corpus used in the evaluation module. When it occurred at least once, the system transformed $A_m$ to $B_m$ and performed the procedure on the next morphology.

where, $k$ is a constant.

Here, we used a simple method using $k$-gram as the environments for calculating to facilitate the experiments. Since we used a simple method, we set $k$ at 2 to increase the precision rate and decrease the recall rate.

We carried out the experiments on sentence compression using newspaper articles. An example of the results are shown in Table 4. The underlined part is the part that was removed in the transformation. Because this section focused on sentence compression, transformation rules to remove strings were frequently used. The “from,” “of flow,” and teki were appropriately deleted, which succeeded in compressing the sentences. But the results also included faulty deletions of to “and,” and surukoto (do). Omitting to changes the original meaning of jigyou to minshushugi, “liberty and democracy”. Omitting surukoto (do) changes a verb youritsu (support) into a noun, and the phrase X-san wo “Mr. X” is missing a
Table 4: Example of sentence compression

| Correctly transformed results                                                                 |
|------------------------------------------------------------------------------------------------|
| kokonoka -kara -no kankoku houmon -dewa                                                     |
| (9th) (from) (of) (Korea) (visit) (in)                                                      |
| rekishi -no nagare -no naka -de                                                            |
| (history) (of) (flow) (of) (middle) (in)                                                    |
| juuoku doru no tsuka teki sochi                                                           |
| (a billion) (dollar) (of) (supplement) (-ary) (step)                                      |
| (a supplementary step of one billion dollars)                                               |

| Incorrectly transformed results                                                              |
|------------------------------------------------------------------------------------------------|
| jiyyu to minshushugi                                                                        |
| (liberty) and (democracy)                                                                   |
| X-san wo kouho to-shite youritsu suru koto wo kimeta                                        |
| (Mr. X) obj (candidate) (as) (support) (do) obj (decide)                                   |
| (decided to support Mr. X as the candidate)                                                 |

verb. The sentence is therefore not grammatical. To correct these errors requires using a new evaluation method that includes syntactic features.

We emphasize that we can compress sentences by using the sentence length as a criterion in the evaluation module, as our experiments confirmed.

5 The case of a sentence-polishing-up system

In this section we describe a sentence-polishing-up system. We used the same 775 transformation rules as in the previous section.

Here, we tried to polish sentences from newspaper articles and applied the following criteria in the evaluation module.

- The substrings of the transformed sentence should occur frequently in the corpora, which contained two-years’ worth of the newspaper articles.

We used the procedures by which we changed part of 2c in the procedures of Section 2 to the following:

(c) The system counts the frequencies of the strings of $S_{1m}A_{m}S_{2m}$ and $S_{1m}B_{m}S_{2m}$ in the corpus used in the evaluation module. When the number of the frequency of $S_{1m}B_{m}S_{2m}$ exceeds that of $S_{1m}A_{m}S_{2m}$, the system transforms $A_{m}$ to $B_{m}$ and performs the procedure of the next morphology.

In this case, too, we used k=2.

We carried out the sentence-polishing experiments using newspaper articles. Some results are shown in Table 5. The lower strings are the transformed ones. The results include sentences that were made more comprehensible by adding “ya and” and “no of”, and others where “mo, meaning “no more than” was added incorrectly. The latter transformation changed the meaning of the sentence. In another case the tense was changed incorrectly form “shita “did” to “saru “do”. These errors resulted from errors in the automatic selection of the transformation rules.

We want to stress that we can perform multiple kinds of paraphrasing by using various types of measures for an evaluation module. The results

10 We need to use a corpus/corpora with the same subject as the target sentence to polish it up accordingly.

11 The research in this section is similar to that on the spelling or word correction (Kukich, 1992). But in the cases of spelling or word correction, ungrammatical sentences are input. In contrast, in sentence-polishing-up systems, grammatical sentences are input and the systems make them more sophisticated. Performing such sentence-polishing-up without the rewriting rules as we automatically extract is difficult.

12 To improve the results of transformation, the frequency of each string $x$ in our procedures must be changed to the probability of occurrence of $x$ in the corpora when the given input data is used as the context. Although our procedures use the fixed $k \times 2$ morphemes of “in front” and “behind” as the context, we should calculate the probabilities by using the variable-length context and more global information, such as syntactic information and tense information, in the powerful probability-estimator such as the maximum entropy method.
of this section included cases where the system enhanced the sentence lengths and modified the input sentences to be more comprehensible; the results were different from the ones obtained in the compression tests. These results thus confirm our assertion.

6 The case of a written-language-to-spoken-language transformation system

Here, we tried to transform the sentences in written-language style to those in spoken-language style.

We carried out new experiments for extracting the rules that transform strings from written to spoken language. These experiments were performed by using the same method as in Section 4 comparing the parallel corpora of written and spoken language. Our institution has been compiling these corpora. The written-language sentences are taken from academic papers and the spoken-language ones from their oral presentations. We obtained 72,835 rewriting rules from these experiments, but many contain the same incorrect rewriting rules as in Section 4. We thus automatically selected 240 rewriting rules that appear more than once. This section uses these rules in the transformation module.

We used the following criteria in the evaluation module.

- The substrings of the transformed sentence should occur frequently in the spoken-language corpora.\footnote{We tried using the 775 rules in Section 4 in addition to these 240 rules for the experiments of this section.}

We followed the same procedure as in the previous section.

We only changed from using a newspaper corpora to a spoken-language corpora. In the previous section, because the subject of the input data was same as that of the corpora used in the evaluation module, the system made the newspaper articles more similar in style to newspaper articles by polishing up. In contrast, in this section, because the input data was in written language and the corpus used in the evaluation module was spoken language, the data was made transformed from written to spoken language.\footnote{These corpora include 330,679 Japanese characters.}

We input sentences from one of our papers as experiments. The results are shown in Table 6.\footnote{We have to use the same-domain corpora with the domain of the target to which input data are transformed.}

In these experiments, no incorrect transformation occurred. *Ma* is a filler and roughly means “so-so.” It is often used in spoken Japanese. *Toiu* means “that is” and is also used often in spoken Japanese. The transformed expressions in the table adequately produced the nuance of spoken Japanese. However, only a few transformed expressions were obtained and the transformation recall rate was low. Therefore, we need to improve the system (Footnote 12).

We want to reiterate that we can perform multiple kinds of paraphrasing by applying various types of criteria in the evaluation module. In these experiments, we obtained expressions used in spoken language. So the results are sufficient to confirm our claim.

7 Conclusion

We demonstrated that a method that transforms sentences based on certain criteria can be used as a universal model for paraphrasing. We showed this with Section 4. However, the results were worse than if we had not used them. This is because the 775 rules included faulty transformation rules such as *suru ⇒ shita* “do ⇒ did”. We believe that if the 775 rules had not included such wrong rules, we could have used them as well for the experiments in this section.

\footnote{The research of this section is very similar to statistical machine translation (Brown et al., 1993). In this section, the source language is written language and the target language is spoken language.}
four ways our systems can apply this simple model and confirmed that by using different criteria we could construct different systems, including question answering, sentence compression, sentence polishing-up, and written-language to spoken-language transformation.

Implementing various types of paraphrases using a universal model has the following advantages:

- Since some components in the model can be used in different types of systems, we can use them to construct more systems after having constructed one.

- We can construct a new paraphrasing system by merely changing a small part of an existing system (e.g., the criteria in the evaluation module). Therefore, we can construct new paraphrasing systems very easily.

In the future, we hope to construct more types of paraphrasing systems by using our universal model.

References

[Brown et al.1993] Peter F. Brown, Stephen A. Della Pietra, Vincent J. Della Pietra, and Robert L. Mercer. 1993. The mathematics of statistical machine translation: Parameter estimation. *Computational Linguistics*, 19(2):263–311.

[Knight and Marcus2000] Kevin Knight and Daniel Marcus. 2000. Statistics-based summarization — step one: Sentence compression. In *Proceedings of AAAI*.

[Kukich1992] Karen Kukich. 1992. Techniques for automatically correcting words in text. *ACM Computing Surveys*, 24(4):377–439.

[Kupiec1993] Julian Kupiec. 1993. MURAX: A robust linguistic approach for question answering using an on-line encyclopedia. In *In Proceedings of the Sixteenth Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*.

[Kurohashi and Nagao1998] Sadao Kurohashi and Makoto Nagao, 1998. Japanes Morphological Analysis System JUMAN version 3.5. Department of Informatics, Kyoto University. (in Japanese).

[Kyokai1985] Nihon Eigo Kyouiku Kyoukai. 1985. Nijunichi Kansei Eiken Nikyu Nijishiken Taisaku (interviewing test). (in Japanese).

[Miller1956] George A. Miller. 1956. The magical number seven, plus or minus two: Some limits on our capacity for processing information. *The Psychological Review*, 63:81–97.

[Murata and Nagao1998] Masaki Murata and Makoto Nagao. 1998. An estimate of referent of noun phrases in Japanese sentences. In *COLING '98*, pages 912–916.

[Murata et al.2001] Masaki Murata, Kiyotaka Uchimoto, Qing Ma, and Hitoshi Isahara. 2001. Magical number seven plus or minus two: Syntactic structure recognition in Japanese and English sentences. In Alexander Gelbukh, editor, *Computational Linguistics and Intelligent Text Processing, Second International Conference, CICLing 2001, Mexico City, February 2001 Proceedings*, pages 43–52. Springer Publisher.

[Ratnaparkhi2000] Adwait Ratnaparkhi. 2000. Trainable methods for surface natural language generation. In *Proceedings of the ANLP-NAACL 2000*.

[TREC-8 committee1999] TREC-8 committee. 1999. Trec-8 question answering track. http://www.research.att.com/~singhal/qa-track.html.

[Yngve1960] Victor H. Yngve. 1960. A Model and an Hypothesis for Language Structure. *the American Philosophical Society*, 104(5):444–466.
