A Comparative Study of Automatic Extraction of Collocations from Corpora: Mutual Information vs. Cost Criteria

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While corpus-based studies are now becoming a new methodology in natural language processing, second language learning offers one interesting potential application. In this paper, we are primarily concerned with the acquisition of collocational knowledge from corpora for use in language learning. First we discuss the importance of collocational knowledge in second language learning, and then take up two measures, mutual information and cost criteria, for automatically identifying or extracting collocations from corpora. Comparative experiments are made between the two measures using both Japanese and English corpora. In our experiments, the cost criteria measure proved more effective in extracting interesting collocations such as fundamental idiomatic expressions and phrases.

KeyWords: *Corpus, Collocations, Mutual Information, Cost Criteria, Second Language Learning*

1 Introduction

Recent rapid advances in computer technology, especially the advent of large storage devices and parallel computers, and numerous data collection efforts have caused a shift in natural language applications from a knowledge-based to a corpus-based or data-intensive approach. The knowledge-based approach focused on abstraction of language, describing linguistic phenomena through minimal core knowledge such as parts-of-speech, syntactic and semantic rules. Linguistic phenomena, however, vary so vastly that they cannot be described through core knowledge. In addition, hand-coding knowledge takes a lot of time and hard work. The knowledge-based approach, therefore, has been found wanting in developing large-scale practical NLP systems.

On the other hand, the corpus-based approach makes no claim about the compactness of the knowledge. Rather, the corpus-based approach derives more power from massive quantities of textual data than from hand-coded knowledge, being able to compensate for the weakness of the knowledge-based approach through authentic examples and various statistics of language use. With the availability of large corpora in recent years, many successful results have

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been derived from corpus-based studies. These include part-of-speech tagging (Kupiec 1992), parsing (Magerman and Marcus 1990), example-based machine translation (Sumita and Iida 1992), statistical machine translation (Brown, Cocke, Pietra, Pietra, Jelinek, Lafferty, Mercer, and Roossin 1993; Brown, Pietra, Pietra, and Mercer 1993), language modeling (Jelinek 1990; Kita 1992) and many other related areas.

One interesting potential use of corpora is for second language learning. Kita et al. (Kita, Hayashi, and Yano 1993a) discussed various way of using corpora in language learning, which includes translation skill acquisition through bilingual corpora, oral/aural skill acquisition through speech corpora, multimedia language learning through structured corpora, and so forth. The greatest advantage of using corpora in language learning is that the corpora provide a body of evidence for the function and usage of words and expressions. At the same time, deriving lexical knowledge from large-scale corpora via automated procedures, as well as its use in language learning CAI systems, is one of the most important issues.

In this paper, we are primarily concerned with the acquisition of collocational knowledge from corpora. In Section 2, we describe why collocational knowledge is important in second language learning. In Section 3, we discuss the automatic extraction of collocations, taking up two measures, mutual information and cost criteria, for identifying or extracting collocations from corpora. In Section 4, we describe comparative experiments in extracting collocations and discuss the two measures.

2 Importance of Collocational Knowledge in Language Learning

There has been much theoretical and applied research on collocations, both from a linguistic and an engineering point of view. Consequently, the definition of collocation differs according to the researcher's interest and standpoint. This paper adopts the most comprehensive definition: a collocation is a cohesive word cluster, including idioms, frozen expressions and compound words.

The importance of collocations has been stressed in an extensive literature. From a language learning viewpoint, it can be summarized as follows:

- In language learning, learners must pay attention to how words are used rather than to individual words by themselves. Collocational knowledge indicates which words co-occur frequently with other words and how they combine within a sentence. Therefore, collocational knowledge is especially effective in sentence generation (Smadja and McK-

eown 1990).

- Collocational knowledge is very difficult to acquire for second language learners. A typical example is the pair of words “strong” and “powerful” (Church, Gale, Hanks, and Hindle 1991; Smadja 1991). These two words have similar meanings, but their usage is quite different. For example, native English speakers prefer saying “strong tea” to “powerful tea”, and prefer saying “powerful car” to “strong car”. For non-natives, however, it is difficult to catch the subtle distinctions between these two words. These lexical preferences were sometimes ignored in the traditional knowledge-based approach; nevertheless they are the most important source for word choice and word ordering.
- It is pointed out that human translation process is based on analogical thinking (Nagao 1984). First, a human translator properly decomposes a sentence into certain fragmental phrases, then s/he translates each fragmental phrase by analogy with other examples, and finally composes fragmental translations into one sentence. Recently, following this idea, example-based machine translations (EBMT) have been widely explored. In some EBMT systems, several kinds of translation knowledge are utilized, such as the string-, pattern-, and grammar-level knowledge types. Collocations are particularly suitable for translation units in either the string- or pattern-level knowledge.
- From a cognitive point of view, it is said that human language acquisition is governed by the law of maximal efficiency (Wolff 1991). In other words, data compression, often called chunking, is performed to minimize storage demands in the brain. A chunk is considered to be a pattern which repeatedly appears in a variety of contexts. Collocations are good candidates for chunk units.

3 Extracting Collocations from Corpora

In the past, several approaches have been proposed to extract collocations from corpora. Church et al. (Church and Hanks 1990; Church et al. 1991) introduced the association ratio, which indicates how strongly two words are related, based on the information-theoretic concept of mutual information. Smadja et al. (Smadja and McKeown 1990; Smadja 1991) take into account word distance as well as word strength for a measure of word association. Also, Basili et al. (Basili, Pazienza, and Velardi 1992) proposed a syntax-based approach. Particularly, mutual information plays a central role in recent lexical statistical research. To take a few examples, Hindle and Rooth (Hindle and Rooth 1993) applied mutual information to disambiguate prepositional phrase attachments, and Brown et al. (Brown, Pietra, deSouza, Lai, and Mercer 1992) used it in determining word classes.

In this section, after surveying how mutual information can be used to extract collocational information, we introduce another measure, called *cost criteria* (Kita, Ogura, Morimoto, and Yano 1993b), to automatically extract interesting collocations from corpora. Comparative experiments and discussions will be described in the next section.

3.1 Mutual Information

The mutual information between two words x and y is defined as follows (Church and Hanks 1990; Church et al. 1991):

$$I(x, y) = \log \frac{P(x, y)}{P(x)P(y)} \quad (1)$$

Here, $P(x)$ and $P(y)$ are word occurrence probabilities, and can be estimated from the number of occurrences of the words, $f(x)$ and $f(y)$, and the number of words in the corpus, N .

$$P(x) = \frac{f(x)}{N} \quad \text{and} \quad P(y) = \frac{f(y)}{N} \quad (2)$$

$P(x, y)$, the joint probability of x and y , is estimated in a similar way.

$$P(x, y) = \frac{f(x, y)}{N} \quad (3)$$

where $f(x, y)$ is the number of occurrences of x followed by y .

The mutual information $I(x, y)$ compares the probability of observing x and y together with the probabilities of observing x and y simply by chance. Thus, a large value indicates that the two words x and y have a strong relationship. By extracting word pairs with large mutual information values, we can obtain common collocations.

Because mutual information values are defined for two words, this simple method can only extract collocations of length two. However, a generalization is suggested in (Jelinek 1990) as follows:

- (1) Start out from the basic vocabulary V_0 . Set $n = 0$.
- (2) Augment the vocabulary V_n by all word sequences " $x y$ " for which $I(x, y) > Thr$, where Thr is a predetermined threshold.
- (3) From Step 2, a new vocabulary V_{n+1} is established.
- (4) Adjust the vocabulary size N to reflect the new vocabulary V_{n+1} .
- (5) Resume from Step 1 with V_{n+1} as its basis.

With this iterative procedure, the final vocabulary includes collocations of arbitrary length.

3.2 Cost Criteria

The cost criteria measure is based on the assumptions that (1) collocations are recurrent word sequences, and (2) the recurrent property is captured by the absolute frequency of a word sequence. However, a simple absolute frequency approach does not work, because the frequency of a sub-sequence is always higher than that of the original word sequence. Therefore, as a measure for identifying or extracting collocations, absolute frequency is not appropriate. Instead, we consider a processing cost for a word sequence, and introduce cost criteria which can quantitatively estimate the extent to which processing is reduced by considering a word sequence as one unit.

Before the presentation of a formal definition, we introduce the following notation:

$$\alpha \quad \cdots \quad \text{a word sequence.} \quad (4)$$

$$|\alpha| \quad \cdots \quad \text{the length of } \alpha. \quad (5)$$

(the number of words in α)

$$f(\alpha) \quad \cdots \quad \text{number of occurrences of } \alpha \text{ in a corpus.} \quad (6)$$

We define a *reduced cost* $K(\alpha)$ for a sequence α as:

$$K(\alpha) = (|\alpha| - 1) \times f(\alpha) \quad (7)$$

$K(\alpha)$ is interpreted as follows. Assume here that, in the corpus, there exists a word sequence α , which is composed of $|\alpha|$ words and occurs $f(\alpha)$ times. Also assume that the cost of processing one word is 1. Similarly, when processing α as a single unit, its processing cost is 1. Here, we assume that: if a word sequence is processed one word at a time, its processing cost is proportional to its length. This assumption is made because of the following reason. We are now concerned with the problem of identifying the sequence α as a collocation. But since this problem is reduced to a string pattern matching problem, it is natural to assume that the cost is proportional to the length of the sequence α . That is, the processing cost for α is $|\alpha|$. By considering α as one unit, the processing cost is reduced to $|\alpha| - 1$. Since α appears $f(\alpha)$ times, we can conclude that the total reduced cost becomes $(|\alpha| - 1) \times f(\alpha)$, which is the definition of $K(\alpha)$.

In reality, however, the problem is not so simple, because word sequences are not mutually disjoint. Consider the case where a word sequence α is a sub-sequence of β (for example, α = “in spite”, β = “in spite of”). Then, we have:

$$f(\alpha) \geq f(\beta) \quad (8)$$

Further, the word sequence α , $f(\beta)$ times out of $f(\alpha)$ times, will be identified as β . Thus, the

actual reduced cost for α is defined as:

$$K(\alpha) = (|\alpha| - 1) \times (f(\alpha) - f(\beta)) \quad (9)$$

Finally, we can extract collocations from a corpus by the following steps:

- (1) Calculate $K(\alpha)$ for each word sequence α in a corpus.
- (2) Rank a word sequence α by using the value $K(\alpha)$.
- (3) Extract higher rank word sequences as collocation candidates.
- (4) Re-calculate $K(\alpha)$ for each α in the collocation candidates. To be more precise, by checking the sequence/sub-sequence relation between every two word sequences in the collocation candidates, modify the $K(\alpha)$ values according to Equation 9.

4 Experiments and Discussions

4.1 The ADD Corpus

In our experiments, the ADD (ATR Dialogue Database) Corpus (Ehara, Ogura, and Morimoto 1990) created by ATR Interpreting Telephony Research Laboratories in Japan was used. The ADD Corpus is a large structured database of dialogues collected from simulated telephone or keyboard conversations which are spontaneously spoken or typed in Japanese or English. This corpus consists of parallel texts of Japanese and English, aligned by utterance. Also, sentences in ADD are morphologically analyzed and annotated with various kinds of syntactic, semantic, and phonological information.

Currently, the ADD Corpus contains textual data from two tasks (text categories); one consists of simulated dialogues between a secretary and participants at international conferences (Conference Task), and the other of simulated dialogues between travel agents and customers (Travel Task).

In our experiments, we used the keyboard dialogues from the Travel Task, which include approximately 120,000 Japanese words and 100,000 English words. The telephone dialogue include linguistic phenomena, such as filled pauses (“ah”, “uh”, etc.), restarts (repeating a word or phrase) and interjections, so we did not use them for our experiments. The aim in our research is to extract linguistically neat expressions, thus we excluded telephone dialogues from the experiments.

4.2 Results and Discussions

Table 1 shows some interesting Japanese collocations extracted using respectively mutual information and cost criteria. Table 2 shows some English ones. In these tables, collocations

are listed in descending order with respect to their values (i.e. mutual information or cost reduction values).

In the experiments, we examined word sequences up to a 10 word length. When using mutual information, the threshold was set to 0.0. This means that we calculated mutual information values for all the word sequences which appeared in the corpus. When using cost criteria, we generated approximately 10,000 collocation candidates. The collocations listed in the tables were selected manually from the higher ranked ones.

Before discussing the results, we first overview the characteristics of Japanese phrases. In general, the order of major constituents in a Japanese sentence is rather free. However, predicate phrase positioning is dominated by the so-called predicate-phrase ending constraint: a predicate phrase appears at the end of its clause. Furthermore, a predicate phrase often has a complex form, consisting of a main predicate such as a verbal noun, verb or adverb, combinations of auxiliary predicates, and a sentence-final particle. These auxiliary predicates and sentence-final particles add various complementary meanings to a sentence, such as honorific, causative, and prohibitive meanings, etc.

As can be seen from the experimental results (Table 1), the method based on mutual information tends to extract task-dependent compound noun phrases, while cost criteria tends to extract complex predicate phrase patterns. Almost all the collocations extracted are in this category. For example, the collocations “desho u ka” and “desu ka”, which had a high cost reduction, are used very often to make interrogative sentences in Japanese. The collocation “tai no desu ga” is usually used to express a speaker’s request, whose meaning is “(I) would like to”.

The comments above are also true of the English data. Mutual information tends to extract compound noun phrases, while cost criteria tends to extract frozen phrase patterns such as “thank you very much” and “I would like to”.

Why does mutual information fail to extract these patterns? Here, let us take “I will” as an illustrative example, which has been picked out by cost criteria (“I will” is omitted from Table 2) but not by mutual information. In our corpus, “I” occurs 2,907 times, “will” occurs 920 times, and “I will” occurs 264 times. Therefore, we have

$$\begin{aligned} I(I, \text{will}) &= \log \frac{\frac{264}{100,000}}{\frac{2907}{100,000} \frac{920}{100,000}} \\ &= 3.3 \end{aligned} \tag{10}$$

This value is not so large, so the two words “I” and “will” cannot be considered to have a significant relationship.

According to the same reasoning, patterns such as “I would like to” and “thank you very much” are excluded as collocation candidates. However, in the ADD Corpus, more than fifty per cent of the sentences that involve the word “would” are subsumed under the pattern “(I would like to ~)”. Therefore, this pattern should be included in the collocation list.

Another drawback using mutual information is the sparseness of data. A corpus cannot provide sufficient data about every word-word relationship. Some word pairs may have high mutual information values in spite of their low frequency in the corpus. For example, the first ranked collocation was “yacht harbor”, which occurs only twice in the ADD Corpus. On the contrary, since the cost criteria measure is based on absolute frequency, such phenomena never happens.

Now, let us consider why mutual information tends to extract task-dependent compound nouns. As noted above, mutual information values become unstable for low-frequency words. Consequently, even if the incidence of a word pair occurring is low, it is quite possible that the mutual information value becomes greater. These low-frequency words, however, often depend on the topic of the text. This is one reason why mutual information tends to extract task-dependent compound nouns.

5 Conclusion

With the growing availability of large textual resources, corpus-based studies are gaining more and more attention among computational linguists and computer scientists. In particular, automatic acquisition of lexical knowledge from corpora is one of the most important and interesting issues. In this paper, we have taken up the problem of how to acquire collocational knowledge and discussed its importance for language learning. We have also described comparative experiments using mutual information and cost criteria. Our experiments demonstrated that mutual information tends to extract task-dependent compound noun phrases, while cost criteria tends to extract predicate phrase patterns.

Unfortunately, the current implementation can only extract collocations of uninterrupted word sequences. Our next plan is to refine the method to extract collocations of interrupted sequences, and to utilize lexical information such as parts-of-speech in order to prevent an improper word sequence from being recognized as a collocation. For example, when applying cost criteria to English corpora, unwelcome word pairs, such as “on the”, “for the” or “of the”, are extracted because such pairs occur frequently in the language. However, these word pairs can be excluded by using parts-of-speech information. Also, we hope to incorporate extracted

collocations into a language learning CAI system.

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Reference

- Basili, R., Pazienza, M. T., and Velardi, P. (1992). "A shallow syntactic analyzer to extract word associations from corpora." *Literary and Linguistic Computing*, 7(2), 113–123.
- Brown, P. F., Cocke, J., Pietra, S. A. D., Pietra, V. J. D., Jelinek, F., Lafferty, J. D., Mercer, R. L., and Roossin, P. S. (1990). "A statistical approach to machine translation." *Computational Linguistics*, 16(2), 79–85.
- Brown, P. F., Pietra, S. A. D., Pietra, V. J. D., and Mercer, R. L. (1993). "The mathematics of statistical machine translation: Parameter estimation." *Computational Linguistics*, 19(2), 263–311.
- Brown, P. F., Pietra, V. J. D., deSouza, P. V., Lai, J. C., and Mercer, R. L. (1992). "Class-based n -gram models of natural language." *Computational Linguistics*, 18(4), 467–479.
- Church, K. W., Gale, W., Hanks, P., and Hindle, D. (1991). "Using statistics in lexical analysis." In Zernik, U. (Ed.), *Lexical Acquisition: Exploiting On-Line Resources to Build a Lexicon*, pp. 115–164. Lawrence Erlbaum Associates.
- Church, K. W., and Hanks, P. (1990). "Word association norms, mutual information, and lexicography." *Computational Linguistics*, 16(1), 22–29.
- Ehara, T., Ogura, K., and Morimoto, T. (1990). "ATR dialogue database." In *Proc. of the 1990 International Conference on Spoken Language Processing*, pp. 1093–1096.
- Hindle, D., and Rooth, M. (1993). "Structural ambiguity and lexical relations." *Computational Linguistics*, 19(1), 103–120.
- Jelinek, F. (1990). "Self-organized language modeling for speech recognition." In Waibel, A., and Lee, K. F. (Eds.), *Readings in Speech Recognition*, pp. 450–506. Morgan Kaufmann Publishers.
- Kita, K. (1992). *A Study on Language Modeling for Speech Recognition*. Ph.D. thesis, Waseda

University.

- Kita, K., Hayashi, T., and Yano, Y. (1993a). "Corpus-based language learning: Towards practical language learning systems." In *Proc. of the 1993 International Conference on Computers in Education*, pp. 355–357.
- Kita, K., Ogura, K., Morimoto, T., and Yano, Y. (1993b). "Automatically extracting frozen patterns from corpora using cost criteria." *Transactions of Information Processing Society of Japan*, 34(9), 1937–1943. (in Japanese).
- Kupiec, J. (1992). "Robust part-of-speech tagging using a hidden Markov model." *Computer Speech and Language*, 6, 225–242.
- Magerman, D. M., and Marcus, M. P. (1990). "Parsing a natural language using mutual information statistics." In *Proc. of the Eight National Conference on Artificial Intelligence*, pp. 984–989.
- Nagao, M. (1984). "A framework of a mechanical translation between Japanese and English by analogy principle." In Elithorn, A., and Banerji, R. (Eds.), *Artificial and Human Intelligence*, pp. 173–180. Elsevier Science Publishers.
- Smadja, F. A. (1991). "Macrocoding the lexicon with co-occurrence knowledge." In Zernik, U. (Ed.), *Lexical Acquisition: Exploiting On-Line Resources to Build a Lexicon*, pp. 165–189. Lawrence Erlbaum Associates.
- Smadja, F. A., and McKeown, K. R. (1990). "Automatically extracting and representing collocations for language generation." In *Proc. of the 28th Annual Meeting of the Association for Computational Linguistics*, pp. 252–259.
- Sumita, E., and Iida, H. (1992). "Example-based NLP techniques: A case study of machine translation." In *Proc. of the AAAI Workshop on Statistically-Based NLP Techniques*, pp. 90–97.
- Wolff, J. G. (1991). *Towards a Theory of Cognition and Computing*. Ellis Horwood.

Table 1 Some examples of extracted collocations. (Japanese)

Mutual Information	Cost Criteria
ichi ryuu no orchestra ni yoru ensou	desho u ka
Jouzankei-onsen to set ni nat ta golf-pack	desu ka
Kunitachi-shi Ishida	desho u
chijou e	mashi ta
night-tour ya dinner-show	sou desu
kaihatsu ga sakan	sou desu ka
buchou ya kachou	to iu koto
6 mai tsuzuri	sou desu ne
hizuke henkou sen wo koe	masu ka
moushikomi kin toshite o azukari	desu ne
Shinjuku-ku Naitou-chou 1 banchi	o negai shi masu
kokunai sen no daiya	itashi masu
hakkou kaisha ni teishutsu	o negai itashi masu
Kenya Tanzania Safari	to omoi masu
yuuran sen no senchou	te ori masu
kaisui yoku	tai no desu ga
yuukyuu kyuuka	wakari mashi ta
Matsushima-wan meguri	kashikomari mashi ta
resort kaihatsu	ni nari masu
umi to yama	to iu no ha
yuujin no hahaoya	shi tai no desu ga
Hachiman-daira Towada Hiraizumi	to iu koto de
danjo betsu no uchiwake	na n desu ga
hakubutsu kan	shi tai no desu
dou nenpai	shouchi itashi mashi ta
senmon yougo	to iu koto desu
yuukou kigen	sou na n desu
genkin kakitome	arigatou gozaimashi ta
Shanghai Sian	sa se te itadaki masu
Setagaya-ku Kyoudou	o mata se itashi mashi ta
seinen gappi	sou na n desu ka
moyori no eki	shitsurei itashi masu
choushoku to chuushoku	yoroshii desho u ka
Fuji-ginkou honten	ka mo shire mase n
gouka kyakusen	irasshai masu ka

Table 2 Some examples of extracted collocations. (English)

Mutual Information	Cost Criteria
yacht harbor	is that so
Echigo Yuzawa	thank you very much
Fifth Avenue	I would like to
General Affairs	I see
Mitsuboshi trading	my name is
slide projector	sorry to have kept you waiting
strong background	is that right
cross the International Date	in that case
the F1 Grand Prix	I understand
Shiretoko Sightseeing Boat Inc.	thank you for
it's my pleasure	do you have any
at the Hotel New Tanda	good bye
give a speech	would you like to
head Mr. Kuwata	I am very sorry
wine production	a little
Wall Street	be able to
jazz dance	I got it
my mother in law	I'll be waiting for your call
to the historic sites	may I have your name and address
I am not that familiar	how much
Keirin and Peking	all right
cause the inconvenience	as soon as possible
holding a paper	then would you give me your
baths and toilets	the other day
Las Vegas	make the reservations
Queen Elizabeth	a lot of
Main Branch	I will call you
Sales Department	that's right
self introduction	how about
zip code	at that time
international cards	the application fee
to the Grand Canyon	is that okay
The Hyatt Regency	I appreciate your
flight number JS	of course
Canadian Rockies and Vancouver	so please hold the line

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