Entropy as an Indicator of Context Boundaries —An Experiment Using a Web Search Engine—

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Abstract. Previous works have suggested that the uncertainty of tokens coming after a sequence helps determine whether a given position is at a context boundary. This feature of language has been applied to unsupervised text segmentation and term extraction. In this paper, we fundamentally verify this feature. An experiment was performed using a web search engine, in order to clarify the extent to which this assumption holds. The verification was applied to Chinese and Japanese.

1 Introduction

The theme of this paper is the following assumption:

> The uncertainty of tokens coming after a sequence helps determine whether a given position is at a context boundary. (A)

Intuitively, the variety of successive tokens at each character inside a word monotonically decreases according to the offset length, because the longer the preceding character n-gram, the longer the preceding context and the more it restricts the appearance of possible next tokens. On the other hand, the uncertainty at the position of a word border becomes greater and the complexity increases, as the position is out of context. This suggests that a word border can be detected by focusing on the differentials of the uncertainty of branching. This assumption is illustrated in Figure 1. In this paper, we measure this uncertainty of successive tokens by utilizing the entropy of branching (which we mathematically define in the next section).

This assumption dates back to the fundamental work done by Harris [6] in 1955, where he says that when the number of different tokens coming after every prefix of a word marks the maximum value, then the location corresponds to the morpheme boundary. Recently, with the increasing availability of corpora, this characteristic of language data has been applied for unsupervised text segmentation into words and morphemes. Kempe [8] reports an experiment to detect word borders in German and English texts by monitoring the entropy of successive characters for 4-grams. Many works in unsupervised segmentation utilise the fact that the branching stays low inside words but increases at a word or morpheme border. Some works apply this fact in terms of frequency [10] [2], while others utilise more sophisticated statistical measures: Sun et al. [12] use mutual information; Creutz [4] use MDL to decompose Finnish texts into morphemes.

R. Dale et al. (Eds.): IJCNLP 2005, LNAI 3651, pp. 93–105, 2005.

This assumption seems to hold not only at the character level but also at the word level. For example, the uncertainty of words coming after the word sequence, “The United States of”, is small (because the word America is very likely to occur), whereas the uncertainty is greater for the sequence “computational linguistics”, suggesting that there is a context boundary just after this term. This observation at the word level has been applied to term extraction by utilising the number of different words coming after a word sequence as an indicator of collocation boundaries [5] [9].

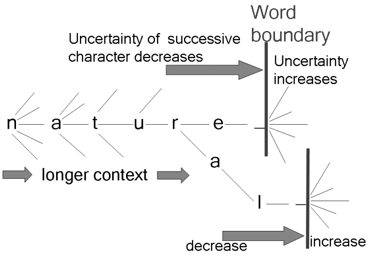


Fig. 1. Intuitive illustration of a variety of successive tokens and a word boundary

As can be seen in these previous works, the above assumption (A) seems to govern language structure both microscopically at the morpheme level and macroscopically at the phrase level. Assumption (A) is interesting not only from an engineering viewpoint but also from a language and cognitive science viewpoint. For example, some recent studies report that the statistical, innate structure of language plays an important role in children’s language acquisition [11]. Therefore, it is important to understand the innate structure of language, in order to shed light on how people actually acquire it.

Consequently, this paper verifies assumption (A) in a fundamental manner. We address the questions of why and to what extent (A) holds. Unlike recent, previous works based on limited numbers of corpora, we use a web search engine to obtain statistics, in order to avoid the sparseness problem as much as possible. Our discussion focuses on correlating the entropy of branching and word boundaries, because the definition of a word boundary is clearer than that of a morpheme or phrase unit. In terms of detecting word boundaries, our experiments were performed in character sequence, so we chose two languages in which segmentation is a crucial problem: Chinese which contains only ideograms, and Japanese, which contains both ideograms and phonograms. Before describing the experiments, we discuss assumption (A) in more detail.

2 The Assumption

Given a set of elements χ and a set of n-gram sequences χ_n formed of χ, the conditional entropy of an element occurring after an n-gram sequence X_n is defined as

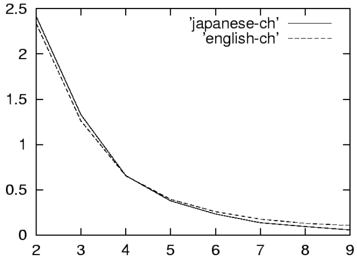


Fig. 2. Decrease in $H(X|X_n)$ for characters when n is increased

$$H(X|X_n) = -\sum_{x_n \in \chi_n} P(X_n = x_n) \sum_{x \in \chi} P(X = x|X_n = x_n) \log P(X = x|X_n = x_n)$$

where $P(X = x)$ indicates the probability of occurrence of x.

A well-known observation on language data states that $H(X|X_n)$ decreases as n increases [3]. For example, Figure 2 shows the entropy values as n increases from 1 to 9 for a character sequence. The two lines correspond to Japanese and English data, from corpora consisting of the Mainichi newspaper (30 MB) and the WSJ (30 MB), respectively. This phenomenon indicates that X will become easier to estimate as the context of X_n gets longer. This can be intuitively understood: it is easy to guess that "e" will follow after "Hello! How ar", but it is difficult to guess what comes after the short string "He".

The last term $-\log\, P(X = x|X_n = x_n)$ in formula above indicates the information of a token of x coming after x_n, and thus the branching after x_n. The latter half of the formula, the local entropy value for a given x_n

$$H(X|X_n = x_n) = -\sum_{x \in \chi} P(X = x|X_n = x_n) \log P(X = x|X_n = x_n), \qquad (1)$$

indicates the average information of branching for a *specific* n-gram sequence x_n. As our interest in this paper is this local entropy, we denote simply $H(X|X_n = x_n)$ as $h(x_n)$ in the rest of this paper.

The decrease in $H(X|X_n)$ globally indicates that given an n-length sequence x_n and another $(n+1)$-length sequence y_{n+1}, the following inequality holds *on average*:

$$h(x_n) > h(y_{n+1}). \qquad (2)$$

One reason why inequality (2) holds for language data is that there is *context* in language, and y_{n+1} carries a *longer context* as compared with x_n. Therefore, if we suppose that x_n is the prefix of x_{n+1}, then it is very likely that

$$h(x_n) > h(x_{n+1}) \qquad (3)$$

holds, because the longer the preceding n-gram, the longer the *same* context. For example, it is easier to guess what comes after x_6="natura" than what comes after x_5 = "natur". Therefore, the decrease in $H(X|X_n)$ can be expressed as the

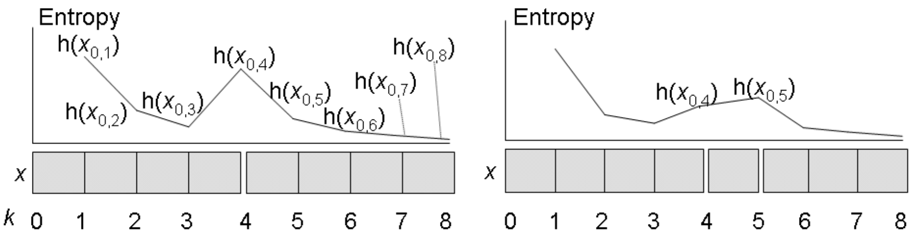


Fig. 3. Our model for boundary detection based on the entropy of branching

concept that if the context is longer, the uncertainty of the branching decreases on average. Then, taking the logical contraposition, if the uncertainty does not decrease, the context is not longer, which can be interpreted as the following:

> If the complexity of successive tokens increases, the location is at the context border. (B)

For example, in the case of x_7 = “natural”, the entropy h(“natural”) should be larger than h(“natura”), because it is uncertain what character will allow x_7 to succeed. In the next section, we utilise assumption (B) to detect the context boundary.

3 Boundary Detection Using the Entropy of Branching

Assumption (B) gives a hint on how to utilise the branching entropy as an indicator of the context boundary. When two semantic units, both longer than 1, are put together, the entropy would appear as in the first figure of Figure 3. The first semantic unit is from offsets 0 to 4, and the second is from 4 to 8, with each unit formed by elements of χ. In the figure, one possible transition of branching degree is shown, where the plot at k on the horizontal axis denotes the entropy for $h(x_{0,k})$ and $x_{n,m}$ denotes the substring between offsets n and m.

Ideally, the entropy would take a maximum at 4, because it will decrease as k is increased in the ranges of $k < 4$ and $4 < k < 8$, and at $k = 4$, it will rise. Therefore, the position at $k = 4$ is detected as the “local maximum value” when monitoring $h(x_{0,k})$ over k. The boundary condition after such observation can be redefined as the following:

B$_{max}$ Boundaries are locations where the entropy is locally maximised.

A similar method is proposed by Harris [6], where morpheme borders can be detected by using the local maximum of the number of different tokens coming after a prefix.

This only holds, however, for semantic units longer than 1. Units often have a length of 1: at the character level, in Japanese and Chinese, there are many one-character words, and at the word level, there are many single words that do not form collocations. If a unit has length 1, then the situation will look like the second graph in Figure 3, where three semantic units, $x_{0,4}$, $x_{4,5}$ $x_{5,8}$, are present, with the middle unit having length 1. First, at $k = 4$, the value of h increases.

At $k = 5$, the value may increase or decrease, because the longer context results in an uncertainty decrease, *though an uncertainty decrease does not necessarily mean a longer context.* When h increases at $k = 5$, the situation would look like the second graph. In this case, the condition B_{max}will not suffice, and we need a second boundary condition:

$\mathrm{B}_{increase}$ Boundaries are locations where the entropy is increased.

On the other hand, when h decreases at $k = 5$, then even $\mathrm{B}_{increase}$cannot be applied to detect $k = 5$ as a boundary. We have other chances to detect $k = 5$, however, by considering $h(x_{i,k})$ where $0 < i < k$. According to inequality (2), then, a similar trend should be present for plots of $h(x_{i,k})$, assuming $h(x_{0,n}) > h(x_{0,n+1})$; then, we have

$$h(x_{i,n}) > h(x_{i,n+1}), \quad \text{for} \quad 0 < i < n. \tag{4}$$

The value $h(x_{i,k})$ would hopefully rise for some i if the boundary at $k = 5$ is important, although $h(x_{i,k})$ can increase or decrease at $k = 5$, just as in the case for $h(x_{0,n})$.

Therefore, when the target language consists of many one element units, $\mathrm{B}_{increase}$is crucial for collecting all boundaries. Note that boundaries detected by $\mathrm{B}_{max}$are included in those detected by the condition $\mathrm{B}_{increase}$.

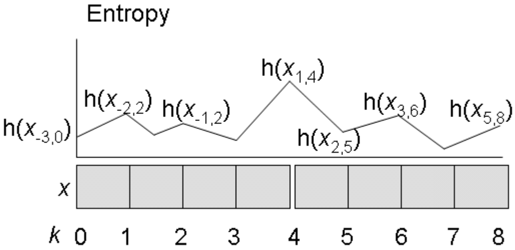


Fig. 4. Kempe's model for boundary detection

Kempe's detection model is based solely on the assumption that the uncertainty of branching takes a local maximum at a context boundary. Without any grounding on this assumption, Kempe [8] simply calculates the entropy of branching for a fixed length of 4-grams. Therefore, the length of n is set to 3, $h(x_{i-3,i})$ is calculated for all i, and the maximum values are claimed to indicate the word boundary. This model is illustrated in Figure 4, where the plot at each k indicates the value of $h(x_{k-3,k})$. Note that at $k = 4$, the h value will be highest. It is not possible, however, to judge whether $h(x_{i-3,i})$ is larger than $h(x_{i-2,i+1})$ in general: Kempe's experiments show that the h value simply oscillates at a low value in such cases.

In contrast, our model is based on the monotonic decrease in $H(X|X_n)$. It explains the increase in h at the context boundary by considering the entropy decrease with a longer context.

Summarising what we have examined, in order to verify assumption (A), which is replaced by assumption (B), the following questions must be answered experimentally:

Q1 Does the condition described by inequality (3) hold?
Q2 Does the condition described by inequality (4) hold?
Q3 To what extent are boundaries extracted by B_{max}or $\mathrm{B}_{increase}$?

In the rest of this paper, we demonstrate our experimental verification of these questions.

So far, we have considered only regular order processing: the branching degree is calculated for *successive* elements of x_n. We can also consider the reverse order, which involves calculating h for the *previous* element of x_n. In the case of the previous element, the question is whether the head of x_n forms the *beginning* of a context boundary. We use the subscripts *suc* and *prev* to indicate the regular and reverse orders, respectively. Thus, the regular order is denoted as $h_{suc}(x_n)$, while the reverse order is denoted by $h_{prev}(x_n)$.

In the next section, we explain how we measure the statistics of x_n, before proceeding to analyze our results.

4 Measuring Statistics by Using the Web

In the experiments described in this paper, the frequency counts were obtained using a search engine. This was done because the web represents the largest possible database, enabling us to avoid the data sparseness problem to the greatest extent possible.

Given a sequence x_n, $h(x_n)$ is measured by the following procedure.

1. x_n is sent to a search engine.
2. One thousand snippets, at maximum, are downloaded and x_n is searched for through these snippets. If the number of occurrences is smaller than N, then the system reports that x_n is unmeasurable.
3. The elements occurring before and after x_n are counted, and $h_{suc}(x_n)$ and $h_{prev}(x_n)$ are calculated.

N is a parameter in the experiments described in the following section, and a higher N will give higher precision and lower recall. Another aspect of the experiment is that the data sparseness problem quickly becomes significant for longer strings. To address these issues, we chose N=30.

The value of h is influenced by the indexing strategy used by a given search engine. Defining $f(x)$ as the frequency count for string x as reported by the search engine,

$$f(x_n) > f(x_{n+1}) \tag{5}$$

should usually hold if x_n is a prefix of x_{n+1}, because all occurrences of x_n contain occurrences of x_{n+1}. In practice, this does not hold for many search engines, namely, those in which x_{n+1} is indexed separately from x_n and an occurrence of x_{n+1} is not included in one of x_n. For example, the frequency count of “mode” does not include that of “model”, because it is indexed separately. In particular,

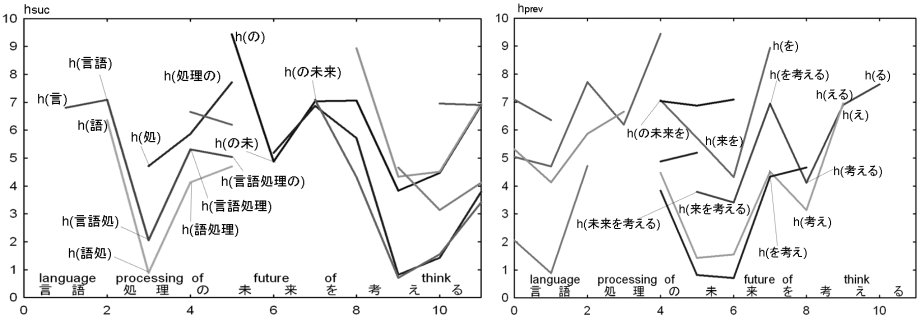


Fig. 5. Entropy changes for a Japanese character sequence (left:regular; right:reverse)

search engines use this indexing strategy at the string level for languages in which words are separated by spaces, and in our case, we need a search engine in which the count of x_n includes that of x_{n+1}. Although we are interested in the distribution of tokens coming after the string x_n and not directly in the frequency, a larger value of $f(x_n)$ can lead to a larger branching entropy.

Among the many available search engines, we decided to use AltaVista, because its indexing strategy seems to follow inequality (5) better than do the strategies of other search engines. AltaVista used to utilise string-based indexing, especially for non-segmented languages. Indexing strategies are currently trade secrets, however, so companies rarely make them available to the public. We could only guess at AltaVistafs strategy by experimenting with some concrete examples based on inequality (5).

5 Analysis for Small Examples

We will first examine the validity of the previous discussion by analysing some small examples. Here, we utilise Japanese examples, because this language contains both phonograms and ideograms, and it can thus demonstrate the features of our method for both cases.

The two graphs in Figure 5 show the actual transition of h for a Japanese sentence formed of 11 characters: $x_{0,11} =$ “ 言語処理の未来を考える”(*We think of the future of* (*natural*) *language processing* (*studies*)). The vertical axis represents the entropy value, and the horizontal axis indicates the offset of the string. In the left graph, each line starting at an offset of $m+1$ indicates the entropy values of $h_{suc}(x_{m,m+n})$ for $n > 0$, with plotted points appearing at $k = m + n$. For example, the leftmost solid line starting at offset $k = 1$ plots the h values of $x_{0,n}$ for $n > 0$, with m=0 (refer to the labels on some plots):

$x_{0,1} =$ 言
$x_{0,2} =$ 言語
...
$x_{0,5} =$ 言語処理の,

with each value of h for the above sequence $x_{0,n}$ appearing at the location of n.

Concerning this line, we may observe that the value *increases* slightly at position $k = 2$, which is the boundary of the word“言語”(*language*). This location will become a boundary for both conditions, $\mathrm{B}_{max}$and $\mathrm{B}_{increase}$. Then, at position $k = 3$, the value drastically decreases, because the character coming after “言語処”(*language proce*) is limited (as an analogy in English, *ssing* is the major candidate that comes after *language proce*). The value rises again at $x_{0,4}$, because the sequence leaves the context of “言語処理” (*language processing*). This location will also become a boundary whether B_{max}or $\mathrm{B}_{increase}$is chosen. The line stops at $n = 5$, because the statistics of the strings $x_{0,n}$ for $n > 5$ were unmeasurable.

The second leftmost line starting from $k = 2$ shows the transition of the entropy values of $h_{suc}(x_{1,1+n})$ for $n > 0$; that is, for the strings starting from the second character “語”, and so forth. We can observe a trend similar to that of the first line, except that the value also increases at 5, suggesting that $k = 5$ is the boundary, given the condition $\mathrm{B}_{increase}$.

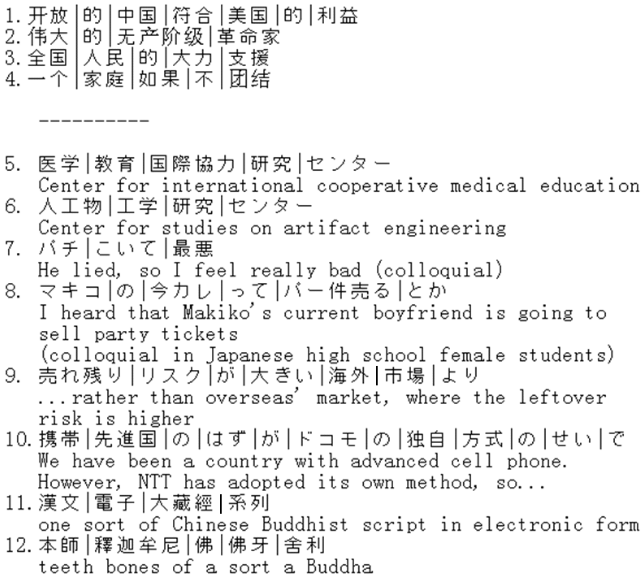
The left graph thus contains 10 lines. Most of the lines are locally maximized or become unmeasurable at the offset of $k = 5$, which is the end of a large portion of the sentence. Also, some lines increase at $k = 2$, 4, 7, and 8, indicating the ends of words, which is correct. Some lines increase at low values at 10: this is due to the verb “考える” (*think*), whose conjugation stem is detected as a border.

Similarly, the right-hand graph shows the results for the reverse order, where each line ending at $m - 1$ indicates the plots of the value of $h_{prev}(x_{m-n,m})$ for $n > 0$, with the plotted points appearing at position $k = m - n$. For example, the rightmost line plots h for strings ending with “る” (from $m = 11$ and $n = 10$ down to 5):

$x_{10,11} =$ る
$x_{9,11} =$ える
$\ldots$
$x_{6,11} =$ 来を考える
$x_{5,11} =$ 未来を考える,

where $x_{4,11}$ became unmeasurable. The lines should be analysed from back to front, where the increase or maximum indicates the *beginning* of a word. Overall, the lines ending at 4 or 5 were unmeasurable, and the values rise or take a maximum at $k = 2$, 4 or 7.

Note that the results obtained from the processing in each direction differ. The forward pass detects 2,4,5,7,8, whereas the backward pass detects 2,4,7. The forward pass tends to detect the *end* of a context, while the backward pass typically detects the *beginning* of a context. Also, it must be noted that this analysis not only shows the segmenting position but also the structure of the sentence. For example, a rupture of the lines and a large increase in h are seen at $k = 5$, indicating the large semantic segmentation position of the sentence. In the right-hand graph, too, we can see two large local maxima at 4 and 7. These segment the sentence into three different semantic parts.



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1. 开放|的|中国|符合|美国|的|利益
2. 伟大|的|无产阶级|革命家
3. 全国|人民|的|大力|支援
4. 一个|家庭|如果|不|团结

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5. 医学|教育|国際協力|研究|センター
   Center for international cooperative medical education
6. 人工物|工学|研究|センター
   Center for studies on artifact engineering
7. バチ|こいて|最悪
   He lied, so I feel really bad (colloquial)
8. マキコ|の|今カレ|って|パー件売る|とか
   I heard that Makiko's current boyfriend is going to
   sell party tickets
   (colloquial in Japanese high school female students)
9. 売れ残り|リスク|が|大きい|海外|市場|より
   ...rather than overseas' market, where the leftover
   risk is higher
10. 携帯|先進国|の|はず|が|ドコモ|の|独自|方式|の|せい|で
   We have been a country with advanced cell phone.
   However, NTT has adopted its own method, so...
11. 漢文|電子|大藏經|系列
   one sort of Chinese Buddhist script in electronic form
12. 本師|釋迦牟尼|佛|佛牙|舍利
   teeth bones of a sort a Buddha
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Fig. 6. Other segmentation examples

On these two graphs, questions Q1 through Q3 from §3 can be addressed as follows. First, as for Q1, the condition indicated by inequality (3) holds in most cases where all lines decrease at $k = 3, 6, 9$, which correspond to inside words. There is one counter-example, however, caused by conjugation. In Japanese conjugation, a verb has a prefix as the stem, and the suffix varies. Therefore, with our method, the endpoint of the stem will be regarded as the boundary. As conjugation is common in languages based on phonograms, we may guess that this phenomenon will decrease the performance of boundary detection.

As for Q2, we can say that the condition indicated by inequality (4) holds, as the upward and downward trends at the same offset k look similar. Here too, there is a counter-example, in the case of a one element word, as indicated in §3. There are two one-word words $x_{4,5}$= "の" and $x_{7,8}$= "を", where the gradients of the lines differ according to the context length. In the case of one of these words, h can rise or fall between two successive boundaries indicating a beginning and end. Still, we can see that this is complemented by examining lines starting from other offsets. For example, at $k = 5$, some lines end with an increase.

As for Q3, if we pick boundary condition B$_{max}$, by regarding any unmeasurable case as $h = -\infty$, and any maximum of any line as denoting the boundary, then the entry string will be segmented into the following:

言語 (*language*)|処理 (*processing*)|の (*of*)|未来 (*future*)|を (*of*)|考える (*think*).

This segmentation result is equivalent to that obtained by many other Japanese segmentation tools. Taking B$_{increase}$as the boundary condition, another boundary is detected in the middle of the last verb "考え | る (*think*, segmented at the stem of the verb)". If we consider detecting the word boundary, then this segmentation is incorrect; therefore, to increase the precision, it would be better to apply a threshold to filter out cases like this. If we consider the morpheme level, however, then this detection is not irrelevant.

These results show that the entropy of branching works as a measure of context boundaries, not only indicating word boundaries, but also showing the sentence structure of multiple layers, at the morpheme, word, and phrase levels.

Some other successful segmentation examples in Chinese and Japanese are shown in Figure 6. These cases were segmented by using B_{max}. Examples 1 through 4 are from Chinese, and 5 through 12 are from Japanese, where '|' indicates the border. As this method requires only a search engine, it can segment texts that are normally difficult to process by using language tools, such as institution names (5, 6), colloquial expressions (7 to 10), and even some expressions taken from Buddhist scripture (11, 12).

6 Performance on a Larger Scale

6.1 Settings

In this section, we show the results of larger-scale segmentation experiments on Chinese and Japanese. The reason for the choice of languages lies in the fact that the process utilised here is based on the key assumption regarding the semantic aspects of language data. As an ideogram already forms a semantic unit as itself, we intended to observe the performance of the procedure with respect to both ideograms and phonograms. As Chinese contains ideograms only, while Japanese contains both ideograms and phonograms, we chose these two languages.

Because we need correct boundaries with which to compare our results, we utilised manually segmented corpora: the People's Daily corpus from Beijing University [7] for Chinese, and the Kyoto University Corpus [1] for Japanese.

In the previous section, we calculated h for almost all substrings of a given string. This requires $O(n^2)$ searches of strings, with n being the length of the given string. Additionally, the process requires a heavy access load to the web search engine. As our interest is in verifying assumption (B), we conducted our experiment using the following algorithm for a given string x.

1. Set $m = 0$, n=1.
2. Calculate h for $x_{m,n}$
3. If the entropy is unmeasurable, set $m = m + 1$,$n = m + 2$, and go to step 2.
4. Compare the result with that for $x_{m,n-1}$.
5. If the value of h fulfils the boundary conditions, then output n as the boundary. Set $m = m + 1$, $n = m + 2$, and go to 2.
6. Otherwise, set $n = n + 1$ and go to 2.

The point of the algorithm is to ensure that the string length is not increased once the boundary is found, or if the entropy becomes unmeasurable. This algorithm becomes $O(n^2)$ in the worst case where no boundary is found and all substrings are measurable, although this is very unlikely to be the case. Note that this

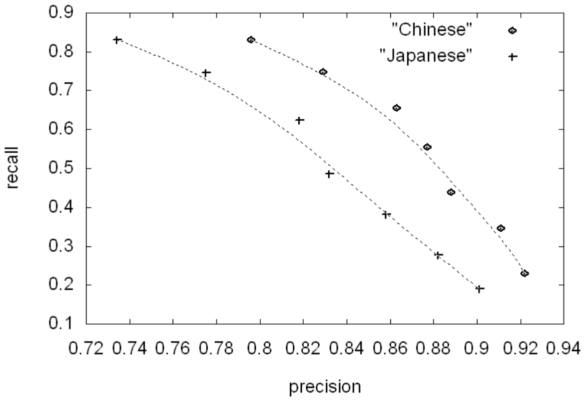

Fig. 7. Precision and recall of word segmentation using the branching entropy in Chinese and Japanese

algorithm defines the regular order case, but we also conducted experiments in reverse order, too.

As for the boundary condition, we utilized $\mathrm{B}_{increase}$, as it includes B_{max}. A threshold *val* could be set to the margin of difference:

$$h(x_{n+1}) - h(x_n) > val. \qquad (6)$$

The larger *val* is, the higher the precision, and the lower the recall. We varied *val* in the experiment in order to obtain the precision and recall curve.

As the process is slow and heavy, the experiment could not be run through millions of words. Therefore, we took out portions of the corpora used for each language, which consisted of around 2000 words (Chinese 2039, Japanese 2254). These corpora were first segmented into phrases at commas, and each phrase was fed into the procedure described above. The suggested boundaries were then compared with the original, correct boundaries.

6.2 Results

The results are shown in Figure 7. The horizontal axis and vertical axes represent the precision and recall, respectively. The figure contains two lines, corresponding to the results for Japanese or Chinese. Each line is plotted by varying *val* from 0.0 to 3.0 with a margin of 0.5, where the leftmost points of the lines are the results obtained for *val*=0.0.

The precision was more than 90% for Chinese with $val > 2.5$. In the case of Japanese, the precision deteriorated by about 10%. Even without a threshold ($val = 0.0$), however, the method maintained good precision in both languages.

The locations indicated incorrectly were inside phonogram sequences consisting of long foreign terms, and in inflections in the endings of verbs and adjectives. In fact, among the incorrect points, many could be detected as correct segmentations. For example, in Chinese, surnames were separated from first names by our procedure, whereas in the original corpus, complete names are regarded as single words. As another example in Chinese, the character “家” is used to indicate “-ist” in English, as in “革命家” (revolutionist) and our process suggested that there is a border in between “革命” and “家” However, in the original corpus, these words are not segmented before “家” but are instead treated as one word.

Unlike the precision, the recall ranged significantly according to the threshold. When *val* was high, the recall became small, and the texts were segmented into larger phrasal portions. Some successful examples in Japanese for *val*=3.0 are shown in the following.

- 地方分権など | 大きな | 課題がある (There are | big | problems | such as power decentralizaion.)
- 今は解散の時期ではない | と考えている (We think that | it is not the time for breakup).

The segments show the global structure of the phrases, and thus, this result demonstrates the potential validity of assumption (B). In fact, such sentence segmentation into phrases would be better performed in a word-based manner, rather than a character-based manner, because our character-based experiment mixes the word-level and character-level aspects at the same time. Some previous works on collocation extraction have tried boundary detection using branching [5]. Boundary detection by branching outputs tightly coupled words that can be quite different from traditional grammatical phrases. Verification of such aspects remains as part of our future work.

Overall, in these experiments, we could obtain a glimpse of language structure based on assumption (B) where semantic units of different levels (morpheme, word, phrase) overlaid one another, as if to form a fractal of the context. The entropy of branching is interesting in that it has the potential to detect all boundaries of different layers within the same framework.

7 Conclusion

We conducted a fundamental analysis to verify that the uncertainty of tokens coming after a sequence can serve to determine whether a position is at a context boundary. By inferring this feature of language from the well-known fact that the entropy of successive tokens decreases when a longer context is taken, we examined how boundaries could be detected by monitoring the entropy of successive tokens. Then, we conducted two experiments, a small one in Japanese, and a larger-scale experiment in both Chinese and Japanese, to actually segment words by using only the entropy value. Statistical measures were obtained using a web search engine in order to overcome data sparseness.

Through analysis of Japanese examples, we found that the method worked better for sequences of ideograms, rather than for phonograms. Also, we observed that semantic layers of different levels (morpheme, word, phrase) could potentially be detected by monitoring the entropy of branching. In our larger-scale experiment, points of increasing entropy correlated well with word borders especially in the case of Chinese. These results reveal an interesting aspect of the statistical structure of language.

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