

Automatic Assessment of Japanese Text Readability Based on a Textbook Corpus

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Abstract

This paper describes a method of readability measurement of Japanese texts based on a newly compiled textbook corpus. The textbook corpus consists of 1,478 sample passages extracted from 127 textbooks of elementary school, junior high school, high school, and university; it is divided into thirteen grade levels and the total size is about a million characters. For a given text passage, the readability measurement method determines the grade level to which the passage is the most similar by using character-unigram models, which are constructed from the textbook corpus. Because this method does not require sentence-boundary analysis and word-boundary analysis, it is applicable to texts that include incomplete sentences and non-regular text fragments. The performance of this method, which is measured by the correlation coefficient, is considerably high ($R > 0.9$); in case that the length of a text passage is limited in 25 characters, the correlation coefficient is still high ($R = 0.83$).

1. Introduction

Assessment of text readability is useful to know whether a text is written at a level suitable for the target audience. For English texts, there are well-known measures such as Flesch Reading Ease and Flesch-Kincaid Grade Level, and they are used for several applications such as compilation of reading materials for students. The Unix command *style* calculates scores of seven different readability measures for a given text.

Recently, we pay much attention to readability of web pages, because the Web is now an important infrastructure of information exchange. Web Accessibility Initiative is working on the draft of “Web Content Accessibility Guidelines 2.0¹”, where the following recommendation is described.

3.1.5 Reading Level: When text requires reading ability more advanced than the lower secondary education level, supplemental content, or a version that does not require reading ability more advanced than the lower secondary education level, is available.

To satisfy the above recommendation, we need a readability measure that produces a *school grade level*.

Readability measures that do not require sentence analysis are preferable for web pages, because they have many incomplete sentences and non-regular text fragments, such as titles, itemized lists, inline figures, and URLs. On the web site *TxReadability*² at the University Texas at Austin, Forecast Grade Level, a no-sentence-analyzing measure, is used for readability measurement of English web pages.

For Japanese texts, a few readability measures have been proposed (Tateisi et al., 1988a; Tateisi et al., 1988b; Shibasaki and Sawai, 2007), none of which is widely used.

It may be because there is little interest in readability in Japan and no software tools are available in public.

In order to fill the lack, we have implemented an easy-to-use tool for readability measurement of Japanese texts. This paper presents a Japanese textbook corpus, which we have compiled as a criterion for readability assessment, and a method of readability measurement by using character-unigram models.

2. Related Work

2.1. Formula-Based Approach

The traditional approach of readability assessment uses *readability formula*, where selected important factors are considered. For example, Flesch Reading Ease (Flesch, 1948) is calculated by the following formula,

$$\begin{aligned} \text{“Flesch Reading Ease”} = \\ 206.835 - 84.6wl - 1.015sl \end{aligned} \quad (1)$$

where *wl* means *word length*, the average number of syllables per word, and *sl* means *sentence length*, the average number of words per sentence. Flesch-Kincaid Grade Level, which translates the above score into a U.S. grade level, is calculated by the following formula.

$$\begin{aligned} \text{“Flesch-Kincaid Grade Level”} = \\ 0.39sl + 11.8wl - 15.59 \end{aligned} \quad (2)$$

To compute these measures correctly, perfect detection of sentence boundaries is required, because they consider sentence length. Some measures do not require such sentence analysis. For example, Forecast Grade Level, which is calculated by the following formula, requires only word-boundary detection.

$$\begin{aligned} \text{“Forecast Grade Level”} = \\ 20 - \frac{\# \text{ of one-syllable words out of 150 words}}{10} \end{aligned} \quad (3)$$

¹<http://www.w3.org/TR/WCAG20/>

²<http://www.lib.utexas.edu:8080/TxReadability/app?service=page/Home>

2.2. Language Modeling Approach

Collins-Thompson and Callan (2004) proposed a *language modeling approach* to predict the readability of English and French texts. This is a classification framework: a class, which corresponds to a grade level of readability, is defined as a sample corpus; the classifier determines the class to which a given text passage is the most similar based on statistical language models (word unigram models) constructed from the sample corpora. The following log-likelihood measure is used for classification,

$$L(G_i|T) = \sum_{w \in T} C(w) \log P(w|G_i) \quad (4)$$

where G_i is a language model for a grade level i , T is a target text passage, $C(w)$ is the count of the word w in T , and $P(w|G_i)$ is the conditional probability of w given G_i .

2.3. Readability Assessment of Japanese Texts

For Japanese texts, a few readability measures have been proposed. Tateisi et al. proposed two formulas (Tateisi et al., 1988a; Tateisi et al., 1988b): one uses ten factors and another simplified one uses six factors. The latter is calculated by the following formula.

$$\begin{aligned} RS = & -0.12ls - 1.37la + 7.4lh - 23.18lc \\ & - 5.4lk - 4.67cp + 115.79 \end{aligned} \quad (5)$$

The six factors are:

ls	average number of characters per sentence
la	average number of Roman letters and symbols per run
lh	average number of Hiragana characters per run
lc	average number of Kanji characters per run
lk	average number of Katakana characters per run
cp	ratio of touten (comma) to kuten (period)

where *run* is a continuous string of the same type of character. This measure requires sentence-boundary detection; but not word-boundary detection, by using runs instead of words.

This formula was used in Hayashi's work (Hayashi, 1992); the web site *TxReadability* also uses this formula for Japanese texts. However, this formula is not familiar to the public and no software tool is provided. Recently, Shibasaki and Sawai (2007) proposed a new formula based on textbooks of the Japanese language in elementary school; it is applicable only to texts in the elementary school level (i.e., Japanese school grade 1–6).

3. Textbook Corpus

As we described above, there are two approaches of readability measurement. Whichever approach we take, we need a text collection called as a *criterion*, which is the basis of readability assessment. The text collection should satisfy at least two requirements: (1) for each text, its readability level is already known; (2) the collection contains texts with broad range of readability levels. Unfortunately, because of little interest in readability in Japan, Japanese texts whose readability levels are explicitly defined are very limited, and no collection fulfill these requirements. Therefore, we have decided to compile a new corpus.

3.1. Textbooks with Twelve Grades

In Japan, textbooks that are used in elementary school, junior high school, and high school must be approved by the Ministry of Education, Culture, Sports, Science and Technology. It means that contents and readability of textbooks are well controlled to follow the government guideline of teaching. For almost every textbook, in which school year (grade level) the textbook should be used is clearly declared. Because of these good characteristics of Japanese textbooks, we decided to use them as a criterion for readability assessment.

The actual compilation process of our textbook corpus is as follows.

1. We obtained a set of textbooks on all subjects except English in all grades. It consists of 111 textbooks in total: 53 textbooks of elementary school (6 years), 25 textbooks of junior high school (3 years), and 33 textbooks of high school (3 years). Their subjects include the Japanese language, mathematics, science, social studies, art, music, home economics.
2. We extracted sample passages from every textbook and stored them electronically by using OCR with manual revision. The size of a sample passage varies according to its grade and subject. In general, we extracted smaller passages from lower grade textbooks, larger passages from higher grade textbooks. It is because the text size per topic becomes larger in higher grade. In total, we extracted 1,167 sample passages; the total number of characters is 710,890.

We call this corpus *twelve-grade textbook corpus* in this paper.

3.2. Thirteenth Grade

There are many documents that are more difficult to read than high school textbooks. This fact suggests that the grade level over the twelfth grade (third year in high school) is necessary for practical application. Therefore, we introduce the thirteenth grade level.

As a criterion for the thirteenth grade level, we use textbooks that are used in the first or second year at university³. In practice, we have selected sixteen textbooks whose subjects correspond to those of high school textbooks; they are used in Nagoya University and Kyoto University. We extracted 311 passages from these textbooks; the total number of characters is 341,016.

Table 1 shows the size of the compiled textbook corpus. We call the whole corpus including the thirteenth grade *thirteen-grade textbook corpus*.

4. Readability Analyzer

4.1. Basic Design

A readability analyzer is a program that estimates readability of a given text. There are a series of requirements and demands for a readability analyzer. For example,

- It can be easily implemented.

³There is no regulation of university textbooks in Japan.

grade	# of samples	# of characters
1	37	10451
2	45	17407
3	70	31204
4	65	21555
5	67	40523
6	62	30020
7	89	70400
8	93	71107
9	78	67243
10	143	94445
11	225	134326
12	193	122209
subtotal	1167	710890
13	311	341016
total	1478	1051906

Table 1: The size of the textbook corpus

- It works fast with light computation.
- It accepts not only regular texts but also web contents. In other words, it is robust for incomplete sentences and non-regular text elements.
- It is stable for texts in broad genres.
- It is less sensitive to passage length. From a short passage, it should produce a reasonable estimation.

Among them, we assigned a high priority to the third requirement, because actual texts are not a collection of regular sentences. Actual texts, especially web pages, include many incomplete sentences and non-regular text fragments such as titles and headlines, itemized lists, formulas, citations, URLs, and other non-regular elements.

Because these elements do not have punctuation marks, perfect automatic sentence-boundary detection is almost impossible. Even if perfect detection is possible, readability formulas that use sentence length as a factor become unreliable because of these short text fragments. This is the reason why a non-sentence-analyzing method, e.g., Forecast Grade Level, is preferable for English web pages than popular formulas that use sentence length, such as Flesch-Kincaid Grade level.

In case of the Japanese language, the situation is worse. Because the Japanese language has no white space between words in written texts, dictionary-based word segmentation is necessary to detect word boundaries. It is well studied and several good tools such as Juman, ChaSen, and Mecab are available, however it is still difficult and unreliable in case that the target text is not a collection of complete sentences. Considering the fact that perfect detection of sentence boundaries on web pages is impossible, we strongly prefer a non-sentence-analyzing and non-word-analyzing method for the Japanese web pages.

Based on the above observation, we have decided to use the language modeling approach, by changing the word unigram model into a character unigram model. This idea comes from the fact that each Kanji character in the Japanese language can be viewed as a pseudo-word.

Three different types of characters are used in the Japanese language: Hiragana, Katakana, and Kanji. Hiragana and Katakana are phonetic characters (alphabets). Students learn all Hiragana and Katakana characters in the first year of elementary school. In contrast, Kanji is ideographic characters: each Kanji character has a unique meaning. The number of Kanji characters is more than 10,000. Students study 1,006 Kanji characters in six years of elementary school, and 989 characters in three years of junior high school.

At actual calculation of the readability, we consider only the limited number of characters: all 83 Hiragana characters, all 84 Katakana characters, and the first-level Kanji characters in JIS X 0208 (2,965 characters). We call them *operative* characters. Other characters (e.g., numbers, Roman alphabets, and rarely used Kanji characters) are ignored.

4.2. Method

Let D_i be a sample corpus for a grade level i . We calculate conditional probability of an operative character x given a language model G_i by the following formula,

$$P(x|G_i) = \frac{C(x, D_i)}{\sum_{z \in D_i} C(z, D_i)} \quad (6)$$

where $C(z, D_i)$ is the count of an operative character z in D_i . In case $P(x|G_i)$ is zero, we apply a simple interpolation: i.e.,

$$P(x|G_i) = \frac{P(x|G_{i-1}) + P(x|G_{i+1})}{2} \quad (7)$$

We repeatedly apply this interpolation until zero probabilities disappear. In case $P(x|G_i)$ is zero for every i , we exclude the character x from the operative characters.

To obtain the readability grade for a given text, we first calculate the log-likelihood value for each grade by using the following formula,

$$L(G_i|T) = \sum_{z \in T} C(z, T) \log P(z|G_i) \quad (8)$$

where z is an operative character in T . In total, we obtain 13 likelihood values; the estimated grade is the grade whose likelihood value is the best among them.

4.3. Four Variants

There are other variants that produce the final estimation from 13 likelihood values. Figure 1 shows 13 likelihood values for a 9-grade text, where the values are normalized such that the average is equal to 0. We may apply smoothing to these values before the final estimation.

In practice, we have implemented four variants:

1. Without smoothing:
Select the best value among 13 likelihood values.
2. With smoothing (degree 2):
Select the best value among 13 smoothed values obtained by fitting a polynomial of degree 2 to 13 likelihood values.

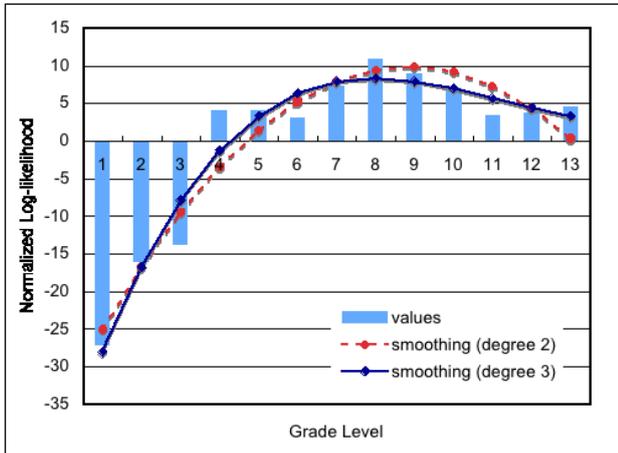


Figure 1: 13 log-likelihood values and their smoothing

3. With smoothing (degree 3):
Same as above except a polynomial of degree 3 instead of a polynomial of degree 2.
4. Median:
Select the median among three estimated grades obtained by the above three variants.

5. Evaluation

To confirm the reliability of our method, we have conducted a series of experiments.

5.1. Leave-One-Out Cross-Validation

First, we have conducted leave-one-out cross-validation for each of sixteen cases, which are the combination of the following settings.

1. corpus
 - (a) the twelve-grade textbook corpus
 - (b) the thirteen-grade textbook corpus
2. variant for final estimation
 - (a) without smoothing
 - (b) with smoothing (degree 2)
 - (c) with smoothing (degree 3)
 - (d) median
3. operative characters
 - (a) Hiragana, Katakana, and Kanji
 - (b) excluding Katakana (i.e., Hiragana and Kanji)

For each case, we have calculated the correlation coefficient (R) and the root mean square error (RMSE) between the actual grade levels and the estimated grade levels. Table 2 shows the result. This table also shows the correlation coefficient when we use Tateisi's formula⁴.

From Table 2, we can see the followings.

⁴In the calculation of Tateisi's formula, we ignore incomplete sentences such as title and header, and non-regular text elements such as mathematical formula.

	corpus			
	12-grade		13-grade	
	R	RMSE	R	RMSE
operative characters = Hiragana, Katakana, and Kanji				
without smoothing	0.883	1.646	0.900	1.620
with smoothing				
(degree 2)	0.888	1.606	0.885	1.794
(degree 3)	0.889	1.697	0.900	1.686
median	0.905	1.459	0.919	1.441
operative characters = Hiragana and Kanji				
without smoothing	0.880	1.661	0.898	1.632
with smoothing				
(degree 2)	0.889	1.596	0.882	1.817
(degree 3)	0.887	1.724	0.898	1.691
median	0.903	1.484	0.916	1.469
Tateisi's formula	-0.758	N/A	-0.758	N/A

Table 2: Result of leave-one-out cross-validations

1. Every variant of our method is superior than Tateisi's formula; the correlation coefficient of our method is over 0.88, while one of Tateisi's formula is around 0.76.
2. The *median* variant is the best among four variants of our method. While smoothing does not always improve the performance, taking the median of three estimated values improves the performance.
3. The performance when Katakana characters are excluded from the operative characters is competitive to the performance when Katakana characters are included.

Table 3 and 4 show the *classification* result of the best case for each corpus. From these tables, we can see that the *classification* accuracy is not high. In case of the thirteen-grade corpus, the ratio of samples whose grade levels are correctly estimated is 39.8%. If we allow plus/minus one level error, the ratio becomes 73.8%. This fact is also confirmed by the fact that RMSE is 1.441.

In summary, overall performance of our readability analyzer is very well ($R > 0.9$); however, each estimated grade is not so accurate (RMSE ≈ 1.5).

5.2. Thirteenth Grade

Next, we have confirmed that introduction of the thirteenth grade does not give a bad influence on the estimation of other grades, because the text sources of the thirteenth grade are different from those of other grades. From Table 4, we calculated the correlation coefficients and RMSEs for the following cases.

1. **Case 1:** 1,167 samples (grade 1–12) are used for validation data, where the output range is between 1 and 13.
2. **Case 2:** 1,167 samples (grade 1–12) are used for validation data, where the output range is between 1 and 12; in other words, in case the output of the readability analyzer is 13, we overwrite it to 12.

grade	estimated grade												total	±0	%	±1	%	
	1	2	3	4	5	6	7	8	9	10	11	12						
1	37	0	0	0	0	0	0	0	0	0	0	0	0	37	37	1.000	37	1.000
2	34	8	2	1	0	0	0	0	0	0	0	0	0	45	8	0.178	44	0.978
3	15	15	17	13	8	2	0	0	0	0	0	0	0	70	17	0.243	45	0.643
4	1	2	10	23	23	5	1	0	0	0	0	0	0	65	23	0.354	56	0.862
5	0	0	2	9	28	25	2	1	0	0	0	0	0	67	28	0.418	62	0.925
6	0	2	0	4	16	23	1	7	5	3	1	0	0	62	23	0.371	40	0.645
7	0	0	0	0	1	10	20	32	18	2	4	2	0	89	20	0.225	62	0.697
8	0	0	0	0	2	9	16	28	18	10	8	2	0	93	28	0.301	62	0.667
9	0	0	0	0	1	6	11	27	15	6	6	6	0	78	15	0.192	48	0.615
10	0	0	0	0	0	6	3	16	32	39	25	22	0	143	39	0.273	96	0.671
11	0	0	0	0	0	1	2	15	23	39	88	57	0	225	88	0.391	184	0.818
12	0	0	0	0	0	0	3	7	15	38	64	66	0	193	66	0.342	130	0.674
total	87	27	31	50	79	87	59	133	126	137	196	155	0	1167	392	0.336	866	0.742

Table 3: Classification result (twelve-grade corpus; median)

grade	estimated grade													total	±0	%	±1	%
	1	2	3	4	5	6	7	8	9	10	11	12	13					
1	37	0	0	0	0	0	0	0	0	0	0	0	0	37	37	1.000	37	1.000
2	29	12	4	0	0	0	0	0	0	0	0	0	0	45	12	0.267	45	1.000
3	10	19	19	12	8	2	0	0	0	0	0	0	0	70	19	0.271	50	0.714
4	1	1	15	19	23	6	0	0	0	0	0	0	0	65	19	0.292	57	0.877
5	0	0	2	8	28	25	3	0	1	0	0	0	0	67	28	0.418	61	0.910
6	0	1	1	6	15	21	3	7	6	2	0	0	0	62	21	0.339	39	0.629
7	0	0	0	0	3	8	21	31	18	3	2	2	1	89	21	0.236	60	0.674
8	0	0	0	0	2	11	14	19	28	13	2	1	3	93	19	0.204	61	0.656
9	0	0	0	0	2	6	9	21	24	10	2	2	2	78	24	0.308	55	0.705
10	0	0	0	0	0	6	3	10	27	42	25	12	18	143	42	0.294	94	0.657
11	0	0	0	0	0	1	1	8	26	63	67	29	30	225	67	0.298	159	0.707
12	0	0	0	0	0	0	2	5	18	60	44	41	23	193	41	0.212	108	0.560
13	0	0	0	0	0	0	0	1	7	15	23	27	238	311	238	0.765	265	0.852
total	77	33	41	45	81	86	56	102	155	208	165	114	315	1478	588	0.398	1091	0.738

Table 4: Classification result (thirteen-grade corpus; median)

Table 5 shows the result. The performance of Case 1 is worse than one of the normal leave-one-out with the twelve-grade corpus, because of the wider output range (i.e., grade 1–13). However, when we tune the output range to 1–12 (Case 2), the performance is competitive to (slightly better than) one of the normal leave-one-out with the twelve-grade corpus.

5.3. Readability Estimation from Short Passages

A desirable characteristic of our method is less sensitivity to passage length. Table 6 shows the correlation coefficients and RMSEs when we restrict the length of the target passages.⁵ Even if we use only the first 25 characters (it approximately corresponds to ten words in English) of each target passage, the correlation coefficient is still high ($R = 0.829$).

5.4. Readability Estimation of Web Pages

The results of the cross-validations described above show our readability analyzer works well within the textbook corpus. Lastly, in this subsection, we describe the readability

estimation of web pages. For all experiments, we use the thirteen-grade corpus as training data and the median variant for the final estimation.

5.4.1. Weekly Kids News

A TV news show named “Shukan Kodomo News (Weekly Kids News)” has a web site⁶, where new stories talked in the TV shows are provided as texts. We have collected 389 news stories from this site; the average size of a news story is about 1,600 characters. The target audience of this TV show is not explicitly announced, however, we estimate that it is junior high school students (grade 7–9).

Table 7 shows the results of readability estimation of 389 stories. The estimated grades of the most of stories fall between 6 and 9; the average is 8.43. This result shows that our readability analyzer works well beyond the textbook corpus.

In this experiment, we found that our analyzer tends to overestimate readability when new stories contain many Katakana characters. Table 7 also shows the result in case we exclude all Katakana characters from the operative characters. By excluding Katakana characters, the readability

⁵In this experiment, we use only 1,286 samples that contain more than 250 characters as validation data.

⁶<http://www.nhk.or.jp/kdns/>

	training data	valid. data	output range	R	RMSE
case 1	13-grade (1478)	1167 (gr. 1–12)	gr. 1–13	0.899	1.514
case 2	13-grade (1478)	1167 (gr. 1–12)	gr. 1–12	0.907	1.440
normal leave-one-out	12-grade (1167)	1167 (gr. 1–12)	gr. 1–12	0.905	1.459

Table 5: Influence of thirteenth grade

passage length (characters)	5	10	15	20	25	50	100	150	200	250
R	0.636	0.750	0.806	0.810	0.829	0.857	0.883	0.897	0.907	0.907
RMSE	2.879	2.308	2.039	2.009	1.918	1.777	1.617	1.506	1.428	1.411

Table 6: Readability estimation from short passages

analyzer becomes stable. We do not have a solid answer why such phenomena is observed at this moment. A possible answer is that the textbook corpus does not contain enough amount of Katakana characters.

5.4.2. Other Web Pages

There are a small number of Japanese web pages in which their target audiences are declared, and finding such pages is not an easy task. By one-day hunting for such pages, we have found 268 pages in 29 sites. They declare that their target audience is any one of elementary school, junior high school, and high school; no exact grade level is described. Table 8 shows the summary of the experiment. From this table, we can see that estimations by our readability analyzer almost agree with readability declarations by web page owners. The phenomena that excluding Katakana characters from the operative characters makes the readability analyzer stable is also observed in this experiment.

6. Software Tool and Web Interface

Our readability analyzer consists of a Perl program and a model file that contains the normalized conditional probabilities of all operative characters of thirteen language models, which are calculated from the thirteen-grade textbook corpus. The program can be executed on a standard Unix environment. We also provide a web interface at <http://kotoba.nuee.nagoya-u.ac.jp> (Figure 2), where you can examine the readability of Japanese texts easily.

Our readability analyzer requires no sentence-analysis and word-analysis; it looks only the limited number of operative characters. This simplicity is useful for practical situations; we just input a raw text file or HTML file in “as is” style.

7. Conclusion

In this paper, we have described a method of readability measurement of Japanese texts based on a newly compiled textbook corpus. The cross-validation experiments have shown that the performance of our method is considerably high measured by the correlation coefficient ($R > 0.9$); in case that the text passages are limited in 25 characters, the correlation coefficient is still high ($R = 0.83$). The other experiments with the web pages show that our method produces reasonable estimations for web texts, which are completely different from textbooks in text type.

The most important characteristic of our method is that it is robust because it does not require any sentence and word-boundary analysis; it is applicable to any Japanese texts in “as is” style.

8. References

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operative characters	pages	estimated grade										
		5	6	7	8	9	10	11	12	13	avg.	σ^2
Hiragana, Katakana, and Kanji	389	1	34	46	106	165	10	15	5	7	8.43	1.83
Hiragana and Kanji	389	2	30	47	137	164	8	0	0	1	8.19	1.01

Table 7: Readability estimation of Weekly Kids News

	pages	estimated grade												
		3	4	5	6	7	8	9	10	11	12	13	avg.	σ^2
operative characters = Hiragana, Katakana, and Kanji														
elementary school (gr. 1-6)	135	2	16	29	21	14	29	16	2	1	3	2	6.73	4.27
junior high school (gr. 7-9)	78				1	5	11	30	17	6	7	1	9.38	1.90
high school (gr. 10-12)	55						2	15	20		9	9	10.47	2.32
operative characters = Hiragana and Kanji														
elementary school (gr. 1-6)	135	4	16	30	26	15	28	12	1	1	2		6.40	3.38
junior high school (gr. 7-9)	78				1	5	11	33	18	6	3	1	9.24	1.54
high school (gr. 10-12)	55						3	14	21	3	7	7	10.33	2.07

Table 8: Readability estimation of web pages

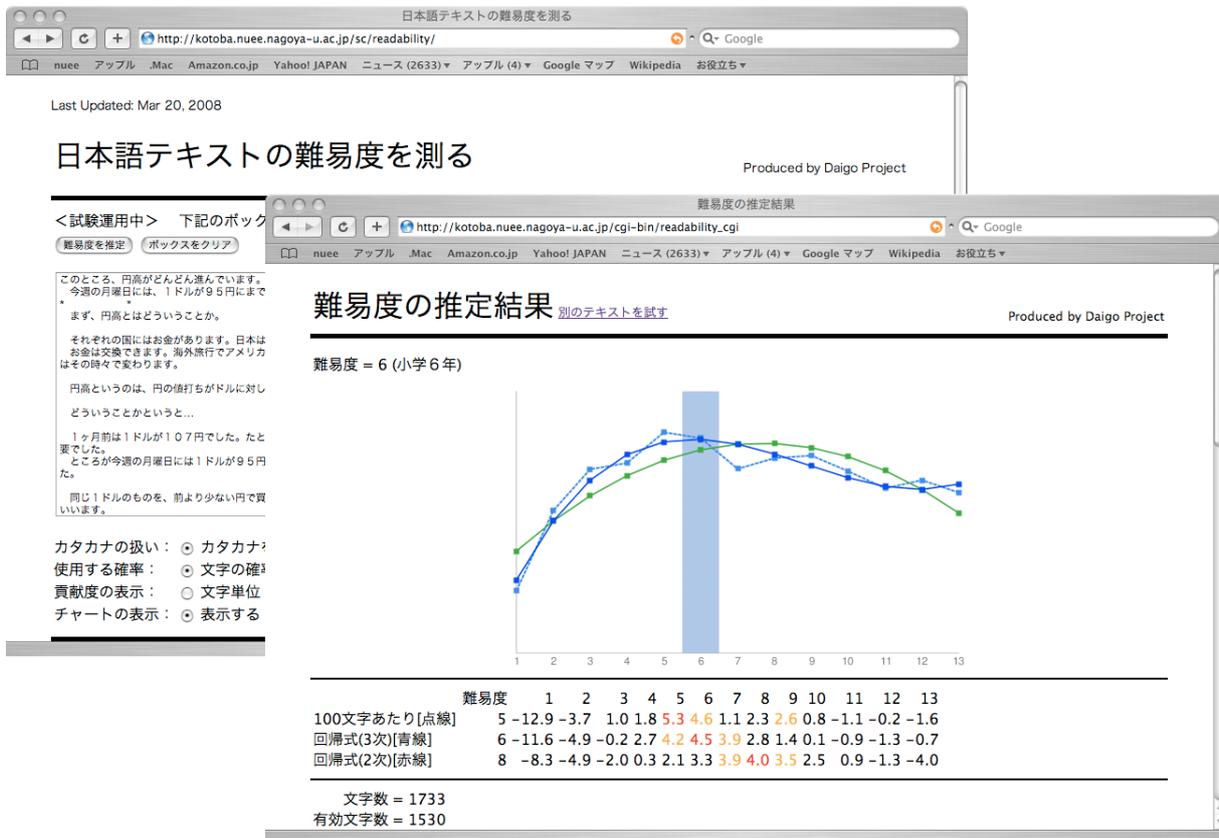


Figure 2: Web interface of readability analyzer