A Study on Classification of English Sentences by the Degree of Difficulty Using Data Mining

Dissertation

A Study on Classification of English Sentences by the Degree of Difficulty Using Data Mining

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and Computer Science

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Chapter 1

Introduction

Since 1990s, English instructions in junior high school and high school has started to emphasize enhancing students' communicative skills. However, there are many reports in news media that Japanese people are not able to communicate in English in practical manner. At the same time, there are worrying sings that students' reading skills are deteriorating. My personal teaching experiences in technical school and junior college also attest this concerning trend.

Although the number of foreign visitors to Japan has increased since 2013, most of people living in Japan do not have many opportunities to communicate with foreigners. The businesses have started to expand their manufacturing centers abroad, starting from South East Asia in 1960s . However, not many business people are required to travel abroad or transfer to foreign offices.

Exponential growth of internet since 1990s allows many people in Japan to acquire the latest information and knowledge. These information and knowledge are mostly written in English. Hence, even those who do not have opportunities to communicate with inbound visitors from abroad or to work in foreign offices, reading English material is essential skills for them to stay productive and competitive in globalized economy.

English instructions in secondary education system with strong emphasis on communicative skills do not fit with this overall situation. In order to nature reading skills, each student is advised to read many English material, in addition to English textbooks. However, it is difficult for the students to find appropriate reading materials which suit their reading skills. In order to find suitable materials, a system which estimates difficulty level automatically and recommend the material to a user is effective in encouraging out of classroom reading activities.

This study attempts to estimate difficulty level of English sentences by using school textbooks used in three countries. The school textbooks are designed so that the difficulty level increases according to grades. The system developed in this study could be applied to reading materials such as magazines and journals.

The study is composed in eight chapters, including this introductory chapter. In Chapter 2, existing studies regarding English sentence classification based on difficulty level are reviewed. In Chapter 3, a new method for building datasets and feature extraction is proposed. In Chapter 4, a two-tier classification method is proposed to improve accuracy in classification. In Chapter 5, the methods proposed in Chapter 3 and Chapter 4 are applied to wider grades. In Chapter 6, school textbooks used in Japan and South Korea are analyzed by using the proposed method. In Chapter 7, discriminant analysis is applied to university students' reading skills. In Chapter 8, conclusions are summarized with description about future application of the proposed system.

Chapter 2

Review of existing studies

2.1 Introduction

There are several existing studies to estimate difficulty level of given English sentences using school textbook data. These various studies can be classified into two according to their approaches to the estimation. One group of studies uses readability formulas. The other group of studies uses machine learning method for estimating the difficulty level. In this chapter, these two groups are reviewed for their strength and weakness.

2.2 Readability approaches

Readability formulas, which estimate how understandable written texts are, started to attract researchers' attentions since late 1920s in the United States. Since then, numerous studies have been done for various purposes. Finding a textbook appropriate for certain age group so that these students were able to enjoy reading was one of the most practical reason for the analysis [1].

For English education in Japan, there are several studies have been conducted using school textbooks. Chujo et al. used four indices to measure the difficulty level of English and Japanese text sample [2]. The samples were composed of 36 articles and books of which 6 were school textbooks. Two indices were related to English texts: 1) the readability of English texts and 2) the percentage of words not covered in school textbooks. Their approach for classifying the texts according to difficulty level was mainly on readability scores. They applied correlational analysis on the four indices. However, their overall approach was not systematic: they listed 36 samples according to the readability score.

Chujo et al. calculate the difficulty of English texts by using readability scores and vocabulary acquisition grades [2]. The samples were composed of 34 school books from four countries: Japan, China, South Korea and Taiwan. Their approach was again not systematic and no accuracy score nor F-value was calculated.

2.3 Machine learning approaches

There are not many studies to estimate difficulty level of school textbooks by using machine learning methods.

Ban and Oyabu analyzed English textbooks being used in Finland and Japan to compare their difficulty level based on words occurrence. From the analysis, several features such as average word length and number of words per sentence were extracted. [4]. Ban et al. used these features extracted from previous study to estimate a difficulty level of English sentences by using machine learning method. The F-value was 0.639 [5]

2.4 Conclusions

The existing studies using readability formulas were simple to understand. However, they were not systematic enough to predict the difficulty level accurately. The studies using machine learning were more organized and produced an accuracy score upon which this study is going to develop.

We will expand the result of their studies in chapter 3 to 6.

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Chapter 3

Proposed Method to build datasets and feature extraction

3.1 Introduction

In recent years, English has increasingly gained the importance. Out of world population of approximately 73 billion, 21 billion people live in countries where English is an official or semi-official language [1], making English the most widely spoken language in the world.

In Japan, where English is not used as a semi-official language, there are several developments to promote learning or utilizing the language. In educational realm, since 2014, top-tier universities and high schools are designated respectively as super global universities and super high schools to educate students who will play leading roles in global society [2, 3]. In business realm, since 2010, many listed companies such as Rakuten, Fast Retailing, and Honda Motor have started to introduce English as an official in-house language [4].

Additionally, many people in Japan take various types of certificate exams for various purposes, one of which is for self-cultivation. Table 3.1 shows the three top ranking exams arranged according to the number of examinees. EIKEN and TOEIC, both certificate exams for English, are most popular. This suggests there are huge demand for English learning.

All these developments suggest that, in Japan, English has been given significant priority over other languages. However, English is not a semi-official language. Those who want to be good at English have to study harder compared to people living in countries where English is widely used. In order to study English better, it is important to look at not only amounts of study hours but also methods of learning and teaching. There already exist wide range of studies on English learning which suggest the importance of using study materials appropriate to the proficiency of each learner [5 - 7]. However, it is not easy to know beforehand the exact difficulty level of a given material, making it difficult for each learner to select the material appropriate for his or her proficiency.

Table 3.1 Number of certificate examinees in Japan

	Certificate Exams	Examinees in 2015
1st	EIKEN	3,225,358
2nd	TOEIC	2,779,300
3rd	KANKEN	2,103,271

English textbooks used in school take into account the proficiency of English learners. These school textbooks “are written and edited with proper consideration for the order of learning by meticulously controlling vocabularies and sentence structures for the sake of learners’ aptitude” [5]. Chujo et al. calculate the difficulty of English texts by using readability scores and percentages of words not covered in school textbooks in Japan and UK [6]. Chujo et al. classify difficulty of English textbooks by using corpus data [5]. Ban and Oyabu analyze English textbooks by applying quantitative linguistics method and find features which changes according to grades [8]. Ban et al. use features extracted from this analysis to estimate a difficulty level of English sentences by using machine learning method. The F-value is 0.639 [9]

In this study, by using features extracted from text data of school textbooks as learning data, we propose to develop a system which can classify difficulty levels of English textbooks with improved accuracy compared to the existing studies done by Ban et al. Because of this approach, we do not adopt natural language processing into the model.

3.2 Proposed System

3.2.1 Outline

In this study, classifiers are built by using features extracted from English text and then develop a system to classify difficulty level of given English textbooks. Figure 3.1 shows the process of building classifiers. First, features of English textbooks are extracted to develop training datasets. After building classifiers, the training datasets are used to validate the accuracy of the classifiers. Leave-one-out cross validation method is applied.

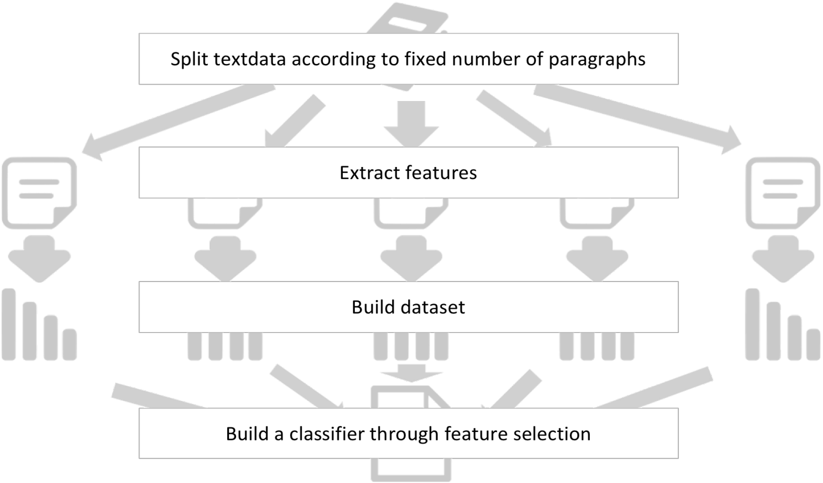

Split textdata according to fixed number of paragraphs
Extract features
Build dataset
Build a classifier through feature selection

Figure3.1 The process of building a classifier

3.2.2 Data Used

Text data from English school textbooks of Finland, Japan and South Korea are used in this study. Table 3.2 lists all the textbooks analyzed in this study. For the textbook used in 3rd grade of South Korea high schools which include both reading and writing sections, only the reading section is used. Hereafter, data will be described by using country and grade, such as “from E3 to E6 in Finland”

Table 3.2 Textbooks used

Title	Grade*	Country**	Year	Publisher***
Wow! 3	E3	FIN	2002	a
Wow! 4	E4	FIN	2003	
Wow! 5	E5	FIN	2005	
Wow! 6	E6	FIN	2006	
KEY 7	J1	FIN	2002	
KEY 8	J2	FIN	2003	
KEY 9	J3	FIN	2004	
NEW HORIZON English Course 1	J1	JPN	2010	b
NEW HORIZON English Course 2	J2	JPN	2010	
NEW HORIZON English Course 3	J3	JPN	2010	
UNICORN ENGLISH COURSE I	H1	JPN	2010	c
UNICORN ENGLISH COURSE II	H2	JPN	2010	
UNICORN ENGLISH COURSE READING	H3	JPN	2010	
MIDDLE SCHOOL ENGLISH 1	J1	KOR	2008	d
MIDDLE SCHOOL ENGLISH 2	J2	KOR	2009	
MIDDLE SCHOOL ENGLISH 3	J3	KOR	2010	
HIGH SCHOOL ENGLISH I	H1	KOR	2009	
HIGH SCHOOL ENGLISH II	H2	KOR	2009	
HIGH SCHOOL ENGLISH READING AND WRITING	H3	KOR	2009	

* E: elementary school, J: Junior High School, H: High school

** FIN: Finland, JPN: Japan, KOR: Korea

*** a: WSOY, b: Tokyo Shuppan, c: Bun-eido, d: Genius Education

3.2.3 Features

Table 3.3 shows features used to generate a dataset. Of 12 features in the table, 10 are used in the study by Ban et al. 2012 [8], and other two are average syllables used to calculate readability score and “average syllables x 84.6” used in Flesch Reading Ease Score, one of the most widely used readability scores.

Table 3.3 Features used in the experiments

Total letters	Average word length
Total letter types	Words / sentence
Total words	Sentences / paragraph
Total word types	Words / word types
Total sentences	Comma / sentence
Average syllables	Average syllables x 84.6

3.2.4 Process of Building Datasets

Figure 3.2 shows a process of building a dataset when 25 paragraphs are used for one instance. First, text data are preprocessed to fit one paragraph data into one line. 25 lines are used as a unit to extract features. Extracted features are aggregated to make dataset. Figure 3.3 shows a sample of text data and extracted features. The dataset produced from the process are partially listed in Figure 3.4. Labels of dataset are manually adjusted for each grade.

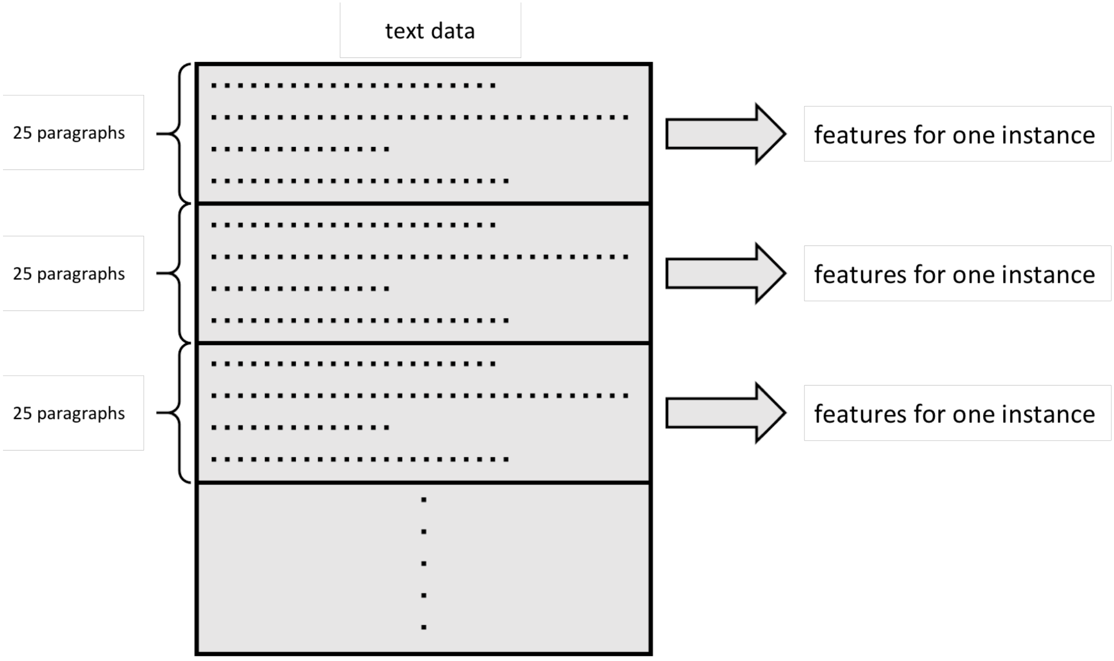
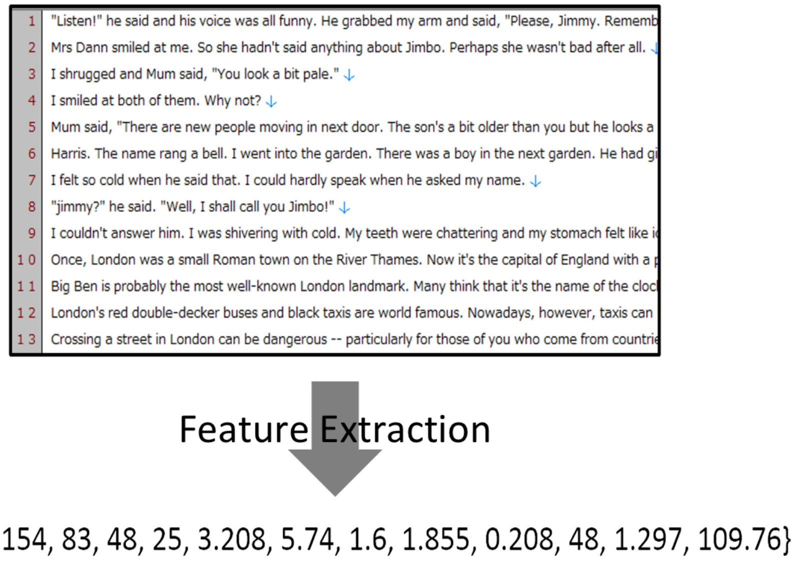

text data
25 paragraphs
25 paragraphs
25 paragraphs
features for one instance
features for one instance
features for one instance

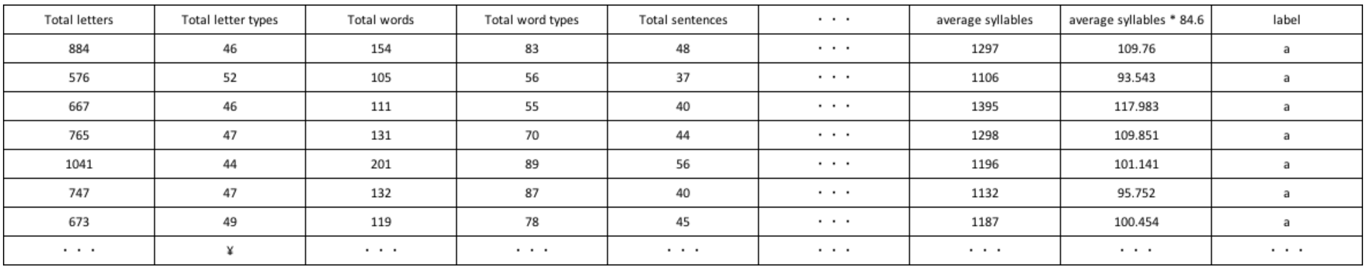
Figure3.2 Process of build dataset



"Listen!" he said and his voice was all funny. He grabbed my arm and said, "Please, Jimmy. Rememb
Mrs Dann smiled at me. So she hadn't said anything about Jimbo. Perhaps she wasn't bad after all.
I shrugged and Mum said, "You look a bit pale."
I smiled at both of them. Why not?
Mum said, "There are new people moving in next door. The son's a bit older than you but he looks a
Harris. The name rang a bell. I went into the garden. There was a boy in the next garden. He had gi
I felt so cold when he said that. I could hardly speak when he asked my name.
"jimmy?" he said. "Well, I shall call you Jimbo!"
I couldn't answer him. I was shivering with cold. My teeth were chattering and my stomach felt like i
Once, London was a small Roman town on the River Thames. Now it's the capital of England with a p
Big Ben is probably the most well-known London landmark. Many think that it's the name of the cloc
London's red double-decker buses and black taxis are world famous. Nowadays, however, taxis can
Crossing a street in London can be dangerous -- particularly for those of you who come from countrie

{ 884, 46, 154, 83, 48, 25, 3.208, 5.74, 1.6, 1.855, 0.208, 48, 1.297, 109.76}

Figure3.3 Feature extraction



Total letters	Total letter types	Total words	Total word types	Total sentences	· · ·	average syllables	average syllables * 84.6	label
884	46	154	83	48	· · ·	1297	109.76	a
576	52	105	56	37	· · ·	1106	93.543	a
667	46	111	55	40	· · ·	1395	117.983	a
765	47	131	70	44	· · ·	1298	109.851	a
1041	44	201	89	56	· · ·	1196	101.141	a
747	47	132	87	40	· · ·	1132	95.752	a
673	49	119	78	45	· · ·	1187	100.454	a
· · ·	¥	· · ·	· · ·	· · ·	· · ·	· · ·	· · ·	· · ·

Figure3.4 Dataset (partial)

3.3 Proposed Method: Refining Process of Dataset building

In an existing study, datasets used in the experiments are generated by extracting features from sentences contained in one page [9]. However, using a page as a unit hinders accurate classification due to the difference in the number of sentences between textbooks for training and those for test. This leads to a less versatile model. To solve this issue, we propose a new method: using a paragraph as a unit and extract data from sentences included in the appropriate number of paragraphs. By using paragraphs as a unit, this method can be applied to wide range of documents beyond textbooks used in the study, possibly leading to a development of system which can classify difficulty of wide range of books.

3.4 Experiments and Validation

Training datasets are loaded to Weka to find feature subsets with the highest feature importance by using a feature selection method. As a feature selection method, brute force search is applied. Random Forest is used to build a model [10], [11]. The feature subsets located by the search are used as training data. To validate the accuracy of classifiers, leave-one-out cross validation is used, since the datasets do not contain sufficient number of instances. Accuracy and F-measure are used as validation indices.

3.5 Experiment

3.5.1 Outline

This experiment aims to find optimum amount of text data required to extract features for one instance used in training dataset. Text data used are from four English textbooks from E3 to E6 grade in Finland. Five datasets are generated according to the number of paragraphs: from 5, 10, 15, 20 and 25.

3.5.2 Results

Table 3.4 shows the results of the experiment. Both accuracy and F-measure are improved with the increase of the number of paragraphs used in one instance. However, there is only a slight improvement between 20 paragraphs and 25 paragraphs. Hence, 20 paragraphs are used as a unit for the analysis. Table 3.5 shows the number of incidents for each grade under 20-paragraph analysis.

Table 3.6 details the classification result of the experiment. There are few instances to misclassify lower grades (E3 and E4) as higher grades (E5 and E6) and vice versa. However, there are more misclassifications between E3 and E4, and between E5 and E6. Table 3.6 shows the selected features in the model which is built by training dataset based on 20 paragraphs as a unit.

Table 3.4 Result of experiment

The number of paragraphs in one instance	accuracy (%)	F-measure
5	52.658	0.525
10	56.853	0.568
15	57.692	0.578
20	64.949	0.650
25	64.935	0.645

Table 3.5 Instances for each grade (Finland elementary school)

Grade	Instances
E3	18
E4	24
E5	28
E6	27

Table 3.6 Result of classification

		Actual grade			
		E3	E4	E5	E6
Predicted grade	E3	14	5	1	0
	E4	3	14	2	0
	E5	1	4	17	9
	E6	0	1	8	18

Table 3.6 Selected features

Total letter types
Total words
Total sentences
Sentences / paragraph
Words / word types

3.6 Conclusions

A certain amount of training data is required to build a classifier. Based on the number of available data, accuracy and F-measure, 20-paragraph is adopted as a proper unit for one instance to run further experiments. Also, compared to the existing study using page as a unit of analysis, this study shows higher F-measure. This result shows that, by using paragraph as a unit of analysis, the system can be developed which not only has wider applicability to many study materials but also can classify with higher accuracy.

Average syllables per word, a feature used in existing readability scores, is not selected by the feature selection. Instead, the number of words per sentence is selected. This result indicates that in primary school, there are little changes in the number of syllables per word and that after junior high school, the number would increase which leads to the rise in difficulty levels. Also, the misclassifications between E3 and E4 and between E5 and E6 indicate that, although the selected features are appropriate to classify data with higher accuracy in general, they are different from features that can classify E3 and E4 and E5 and E6 more accurately.

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Chapter 4

Development of two-tier classification model

4.1 Introduction

The results of the experiments 1 in Chapter 3 have showed several pairs of grades which are mutually misclassified and those which are not misclassified at all. These results indicate that multi-tier classifications by using several models can perform better classification than one-tier, single model classification into four grades. Based on this finding, a second method is proposed in this chapter. Two-tier classification system is constructed with a first stage classifier to perform general classification and second stage classifiers to perform finer classification.

One-tier classification used in the existing study and two-tier classification proposed in this chapter are applied to the following experiments to compare the accuracy of each method.

4.2. Data

Dataset used in Chapter 3 are used in this Chapter.

4.3. Experiment

4.3.1 Outline

The results of experiment in Chapter 3 lead to the hypothesis that feature subsets which can classify accurately between E3 and E4 and between E5 and E6 are different from those that can better classify entire grades. In order to verify the hypothesis, second experiment is conducted. At the first stage, classifier 1 is placed to make binary classification between lower-grade group (E3 or E4) and higher-grade group (E5 or E6). At the second stage, two classifiers, classifier 2 and 3, respectively classify lower-grade group into E3 and E4 and higher-grade group into E5 and E6 to obtain 4 classes. Figure 4.1 shows the process of the two-tier classification.

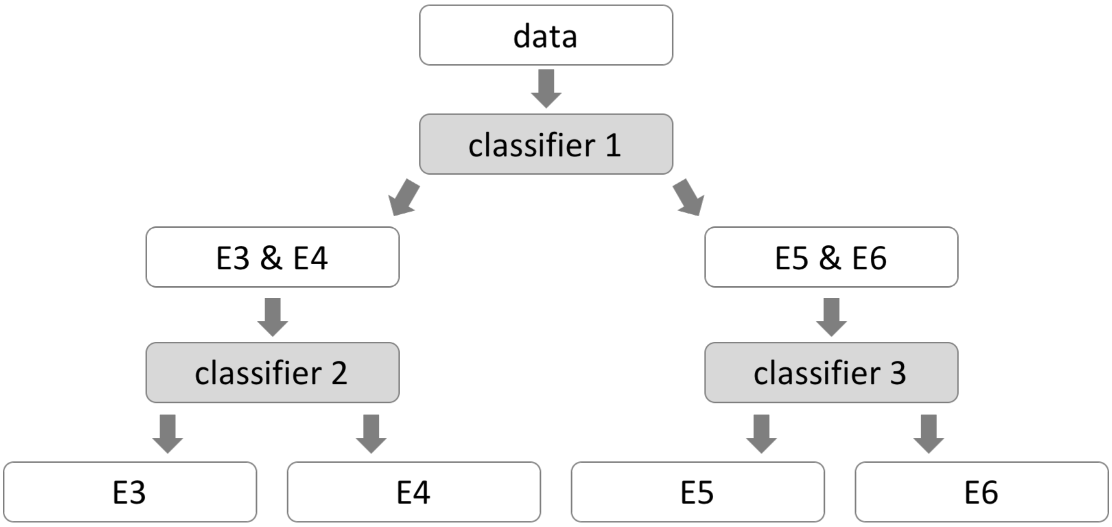


Figure 4.1 Process of two-tier classification for Finland

4.3.2 Results

Table 4.1 shows the results of one-tier classification. Table 4.2 shows the results of first stage classification of two-tier experiment. Table 4.3 shows the final results of the two-tier classification. Table 4.4 shows the comparison of the accuracy and the F-measures of one-tier and two-tier classifications. Two-tier classification shows better result: 7.216 points higher accuracy and 0.072 higher F-measure. This result proves the effectiveness of two-tier classification. Feature subsets selected by the algorithm are listed in bold in Figure 4.2.

Table 4.1 Result of one-tier classification

		Actual grade			
		E3	E4	E5	E6
Predicted grade	E3	14	5	1	0
	E4	3	14	2	0
	E5	1	4	17	9
	E6	0	1	8	18

Table 4.2 Result of first stage classification

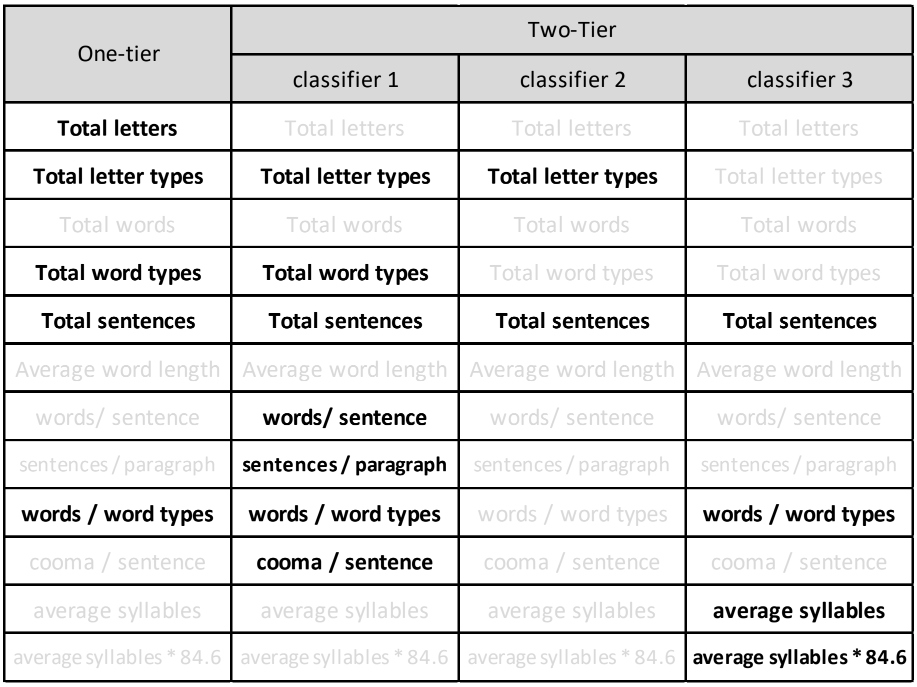
		Actual grades	
		E3 & E4	E5 & E6
Predicted grades	E3 & E4	38	3
	E5 & E6	4	52

Table 4.2 Result of second stage classification

		Actual grade			
		E3	E4	E5	E6
Predicted grade	E3	14	3	1	0
	E4	3	18	2	0
	E5	0	1	20	9
	E6	1	2	5	18

Table 4.3 Result comparison: one-tier vs two-tier

classifier	accuracy (%)	F-measure
One-tier	64.949	0.650
1st / Two-tier	92.784	0.928
2nd / Two-tier	72.165	0.722



One-tier	Two-Tier		
	classifier 1	classifier 2	classifier 3
Total letters	Total letters	Total letters	Total letters
Total letter types	**Total letter types**	**Total letter types**	Total letter types
Total words	Total words	Total words	Total words
Total word types	**Total word types**	Total word types	Total word types
Total sentences	**Total sentences**	**Total sentences**	**Total sentences**
Average word length	Average word length	Average word length	Average word length
words/ sentence	**words/ sentence**	words/ sentence	words/ sentence
sentences / paragraph	**sentences / paragraph**	sentences / paragraph	sentences / paragraph
words / word types	**words / word types**	words / word types	**words / word types**
cooma / sentence	**cooma / sentence**	cooma / sentence	cooma / sentence
average syllables	average syllables	average syllables	**average syllables**
average syllables * 84.6	average syllables * 84.6	average syllables * 84.6	**average syllables * 84.6**

Figure 4.2 Comparison of feature subsets

4.4 Conclusions

Using three classifiers to run two-tire classification to obtain 4 classes results in higher accuracy compared to using one-classifier-single-stage classification, suggesting the effectiveness of the two-tier classification method.

Figure 4.2 shows two types of features: those which function at each classification, such as the total number of sentences in 20 paragraphs, and those which function at specific classification, such as average syllables per one word.

Classifiers 2 and 3 use distinct feature subset, while the subsets of the classifier of one-tier classification and the classifier 1 of two-tier classification are composed of similar features. This result supports the finding in the experiment in Chapter 3 which suggests that feature subsets to classify lower-grade group into E3 and E4 and higher-grade group into E5 and E6 are different from the subsets for classifying data into lower and higher grades.

Chapter 5

Applying two-tier classifier model to wider grade textbooks

5.1 Introduction

The results of Chapter 4 have showed the effectiveness of two-tier classification system proposed in this study. In this Chapter, the proposed system is applied to wider grade textbooks used in Finland. Specifically, in preceding chapters, textbooks used in elementary years were used. In this Chapter, textbooks used in junior high schools are added to the experiment to investigate the robustness of the proposed system.

5.2. Data

Dataset used in Chapter 3 are used in this Chapter.

5.3. Experiment

5.3.1 Outline

This experiment uses dataset for 7 years: from elementary E3 to Junior-High J3 in Finland to run one-tier and two-tier classifications. Dataset are generated by using text based on 20 paragraphs. Table 5.1 shows the number of the instances for each grade. Figure 5.1 shows the process of two-tier classification. At the first stage, the data are classified into three classes: E3 and E4, E5 and E6 and J1 to J3. At the second stage, these three classes are further classified into each grade. Compared to the experiment in Chapter 4, an additional classifier is placed on second stage in order to cope with expansion of textbooks used.

Table 5.1 Instances for each grade (Finland expanded)

Grade	Instances
E3	18
E4	24
E5	28
E6	27
J1	21
J2	27
J3	32

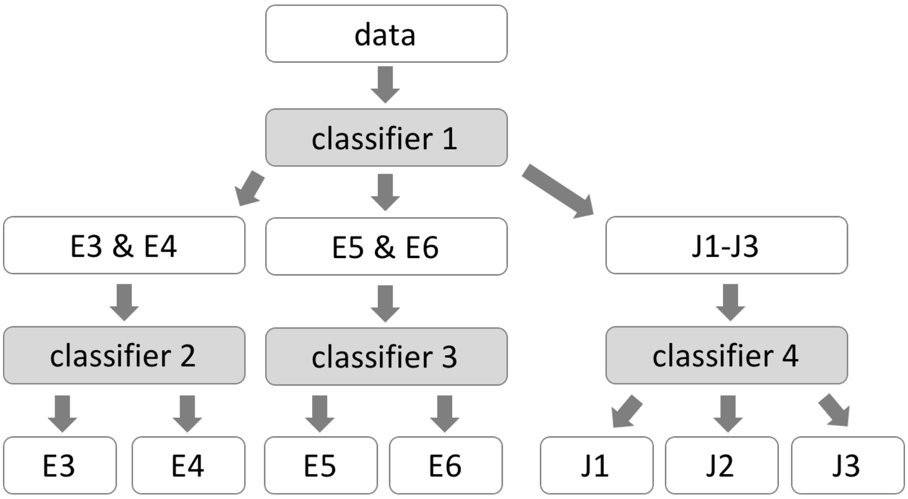


Figure 5.1 Two-tier classification for Finland (expanded)

5.3.2 Results

The results of one-tier and two-tier classifications are respectably shown in Tables 5.2 and 5.3. Table 5.4 shows the final result of the two-tier classification. Table 5.5 shows the comparison of the accuracy and the F-measures of one-tier and two-tier classifications. Feature subsets selected by the algorithm are listed in bold in Figure 5.2.

Table 5.2 Result of the one-tier classification

		Actual grade						
		E3	E4	E5	E6	J1	J2	J3
Predicted grade	E3	11	9	2	0	0	0	0
	E4	4	12	3	0	0	0	0
	E5	2	2	16	8	2	0	2
	E6	1	1	5	12	3	4	1
	J1	0	0	1	2	9	3	2
	J2	0	0	0	4	4	14	7
	J3	0	0	1	1	3	6	20

Table 5.3 Result of the 1st stage classification

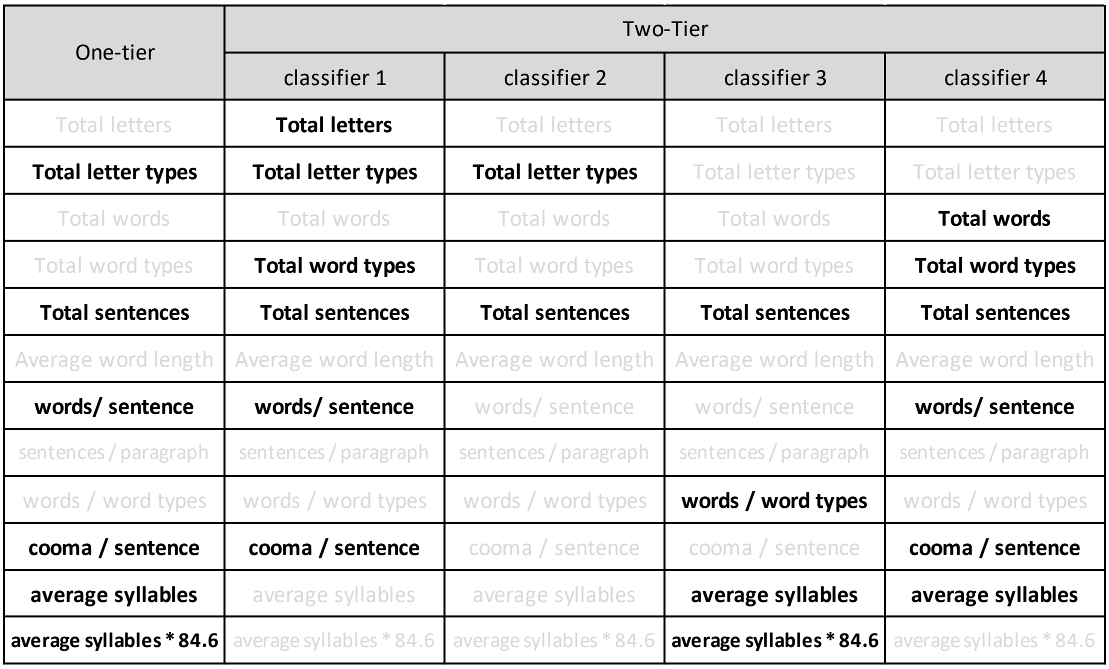
		Actual grades		
		E3 & E4	E5 & E6	J1 - J3
Predicted grades	E3 & E4	38	5	0
	E5 & E6	4	44	6
	J1 - J3	0	6	74

Table 5.4 Result of the 2nd stage classification

		Actual grade						
		E3	E4	E5	E6	J1	J2	J3
Predicted grade	E3	14	3	2	0	0	0	0
	E4	3	18	3	0	0	0	0
	E5	0	1	18	9	3	1	0
	E6	1	2	3	14	1	0	1
	J1	0	0	1	0	8	7	5
	J2	0	0	1	3	4	15	5
	J3	0	0	0	1	6	4	21

Table 5.5 Comparison of the result of experiment

classifier	accuracy (%)	F-measure
One-tier	53.107	0.531
1st / Two-tier	88.136	0.881
2nd / Two-tier	61.017	0.609



One-tier	Two-Tier			
	classifier 1	classifier 2	classifier 3	classifier 4
Total letters	**Total letters**	Total letters	Total letters	Total letters
Total letter types	**Total letter types**	**Total letter types**	Total letter types	Total letter types
Total words	Total words	Total words	Total words	**Total words**
Total word types	**Total word types**	Total word types	Total word types	**Total word types**
Total sentences	**Total sentences**	**Total sentences**	**Total sentences**	**Total sentences**
Average word length	Average word length	Average word length	Average word length	Average word length
words/ sentence	**words/ sentence**	words/ sentence	words/ sentence	**words/ sentence**
sentences / paragraph	sentences / paragraph	sentences / paragraph	sentences / paragraph	sentences / paragraph
words / word types	words / word types	words / word types	**words / word types**	words / word types
cooma / sentence	**cooma / sentence**	cooma / sentence	cooma / sentence	**cooma / sentence**
average syllables	average syllables	average syllables	**average syllables**	**average syllables**
average syllables * 84.6	average syllables * 84.6	average syllables * 84.6	**average syllables * 84.6**	average syllables * 84.6

Figure 5.2 Comparison of feature subsets

5.4 Conclusions

Compared to one-tier classification, two-tier classification yields better result: The accuracy is higher than 60% and F-measure is larger than 0.6. These results show the effectiveness of two-tier classification. Also, the first stage of two-tier classification results in F-measure of 0.881. This high accuracy suggests that this classifier can accurately classify the difficulty of English sentences.

Figure 5.2 lists feature subsets for classifiers used in one-tier and two-tier classifications. Every classifier uses total number of sentences. This result suggests that the number of sentences used in 20 paragraphs changes according to the difficulty level of the textbooks. Also, the feature subsets used in each classifier are different. This result shows the necessity to use multiple classifiers.

Chapter 6

Expanding Proposed Methods to textbooks used in Japan and South Korea

6.1 Introduction

The experiment in Chapter 5 have showed robust results by applying two-tier classifier model to wider school grade textbooks. In this chapter, the model is applied to English textbooks used in Japan and South Korea to investigate the robustness of the model for classifying textbooks used in cultural context different from Finland, on which the model is developed.

6.2 Data

Dataset used in Chapter 3 are used in this Chapter.

6.3 Experiments using textbooks of Japan

6.3.1 Outline

One-tier and two-tier classifications are conducted by using textbook data of Japan. Dataset are produced by using text based on 20 paragraphs. Table 6.1 shows the number of instances for each grade. Figure 6.1 shows the process of two-tier classification. At the first stage, the data are classified into junior high and high school, and at the second stage, each class is further classified into 3 classes.

Table 6.1 Instances for each grade (Japan)

Grade	Instances
J1	11
J2	11
J3	8
H1	8
H2	13
H3	12

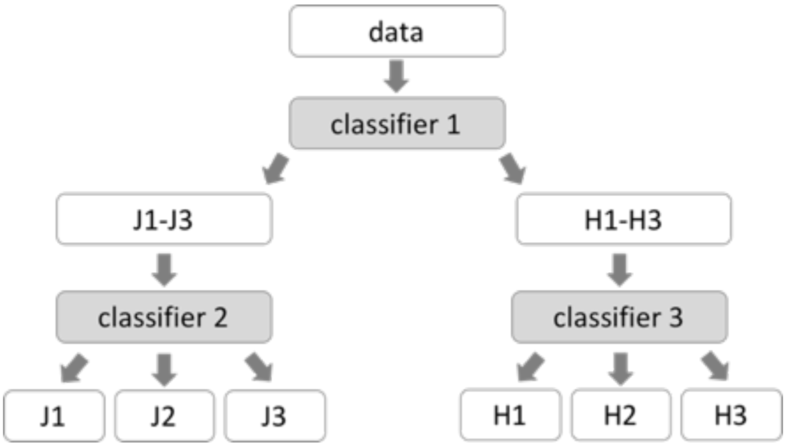


Figure 6.1 Two-tier classification for Japan

6.3.2 Results

Table 6.2 shows the result of one-tier classification. Table 6.3 shows the result of first stage classification of two-tier experiment. Table 6.4 shows the final result of the two-tier classification. The first stage of two-tier classification classifies all the data accurately. Table 6.5 shows the comparison of the accuracy and the F-measures of one-tier and two-tier classifications. Two-tier classification shows higher result: 3.174 points higher accuracy and 0.028 higher F-measure. Feature subsets used by each classifier are listed in bold in Figure 6.2.

Table 6.2 Result of the one-tier classification

		Actual grade					
		J1	J2	J3	H1	H2	H3
Predicted grade	J1	11	1	0	0	0	0
	J2	0	10	2	0	0	0
	J3	0	0	6	0	1	0
	H1	0	0	0	6	3	1
	H2	0	0	0	1	5	3
	H3	0	0	0	1	4	8

Table 6.3 Result of the 1st stage classification

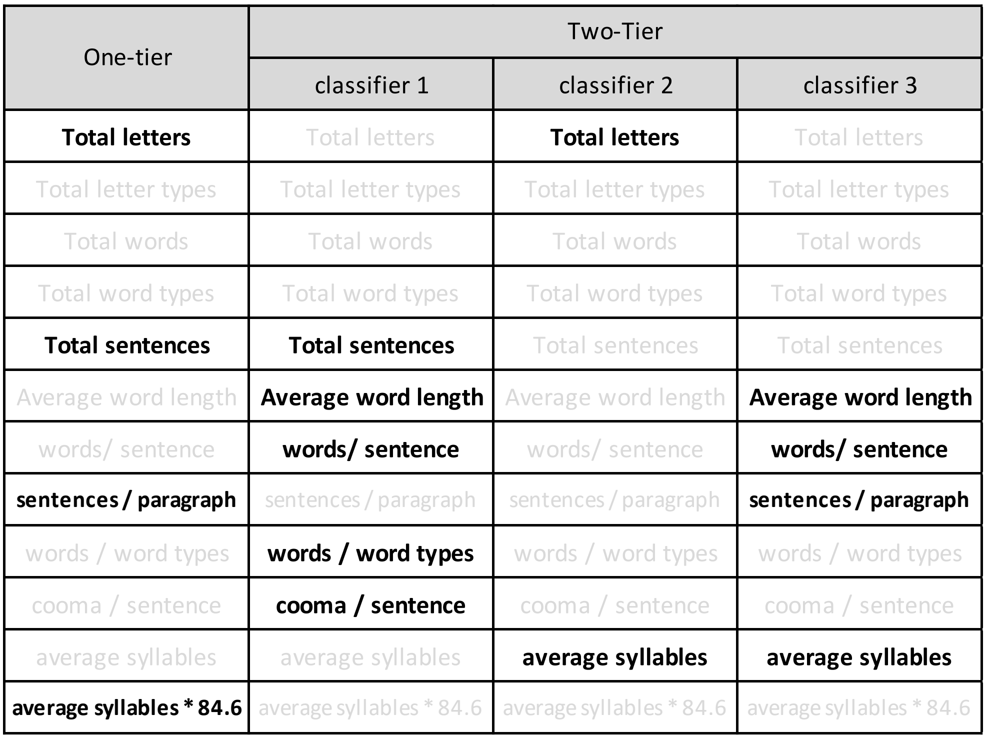
		Actual grades	
		J1 - J3	H1 - H3
Predicted grades	J1 - J3	30	0
	H1 - H3	0	33

Table 6.4 Result of the 2nd stage classification

		Actual grade					
		J1	J2	J3	H1	H2	H3
Predicted grade	J1	11	1	0	0	0	0
	J2	0	10	2	0	0	0
	J3	0	0	6	0	0	0
	H1	0	0	0	6	2	1
	H2	0	0	0	2	9	5
	H3	0	0	0	0	2	6

Table 6.5 Comparison of the result of experiment2

classifier	accuracy (%)	F-measure
One-tier	73.016	0.721
1st / Two-tier	100.000	1.000
2nd / Two-tier	76.190	0.76



One-tier	Two-Tier		
	classifier 1	classifier 2	classifier 3
Total letters	Total letters	**Total letters**	Total letters
Total letter types	Total letter types	Total letter types	Total letter types
Total words	Total words	Total words	Total words
Total word types	Total word types	Total word types	Total word types
Total sentences	**Total sentences**	Total sentences	Total sentences
Average word length	**Average word length**	Average word length	**Average word length**
words/ sentence	**words/ sentence**	words/ sentence	**words/ sentence**
sentences / paragraph	sentences / paragraph	sentences / paragraph	**sentences / paragraph**
words / word types	**words / word types**	words / word types	words / word types
cooma / sentence	**cooma / sentence**	cooma / sentence	cooma / sentence
average syllables	average syllables	**average syllables**	**average syllables**
average syllables * 84.6	average syllables * 84.6	average syllables * 84.6	average syllables * 84.6

Figure 6.2 Comparison of feature subsets

6.3.3 Discussion

Out of 4 classifiers, only the classifier 1 uses "comma per sentence" feature. This result suggests within junior high school years or high school years, this feature value remains without significant changes but between junior high school and high school, the number of comma per sentence greatly varies.

6.4 Experiment using textbooks of South Korea

6.4.1 Outline

One-tier and two-tier classifications are conducted by using textbook data of South Korea. Datasets are produced by using text based on 20 paragraphs. Table 6.6 shows the number of instances for each grade. Two-tier classification is run in the process illustrated in Figure 6.3.

Table 6.6 Instances for each grade (South Korea)

Grade	Instances
J1	22
J2	20
J3	21
H1	17
H2	17
H3	13

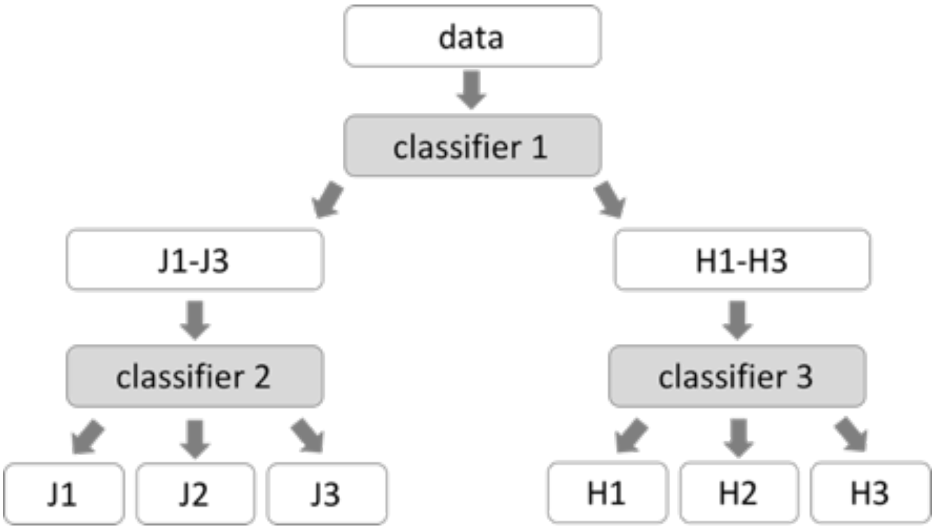


Figure 6.3 Two-tier classification for Japan

6.4.2 Results

Table 6.7 shows the result of one-tier classification. Table 6.8 shows the result of first stage classification of two-tier experiment. Table 6.9 shows the final result of the two-tier classification. Table 6.10 shows the comparison of the accuracy and the F-measures of one-tier and two-tier classifications. Two-tier classification shows higher result: 4.545 points higher accuracy and 0.056 higher F-measure. Adding to this overall high accuracy, the first stage of two-tier classification yields accuracy of 93.636% and F-measure of 0.936. Feature subsets used by each classifier are listed in bold in Figure 6.4.

Table 6.7 Result of the one-tier classification

		Actual grade					
		J1	J2	J3	H1	H2	H3
Predicted grade	J1	18	4	3	0	0	0
	J2	2	13	2	0	3	0
	J3	1	2	14	2	2	3
	H1	0	0	1	10	3	6
	H2	1	1	0	4	8	2
	H3	0	0	1	1	1	2

Table 6.8 Result of the 1st stage classification

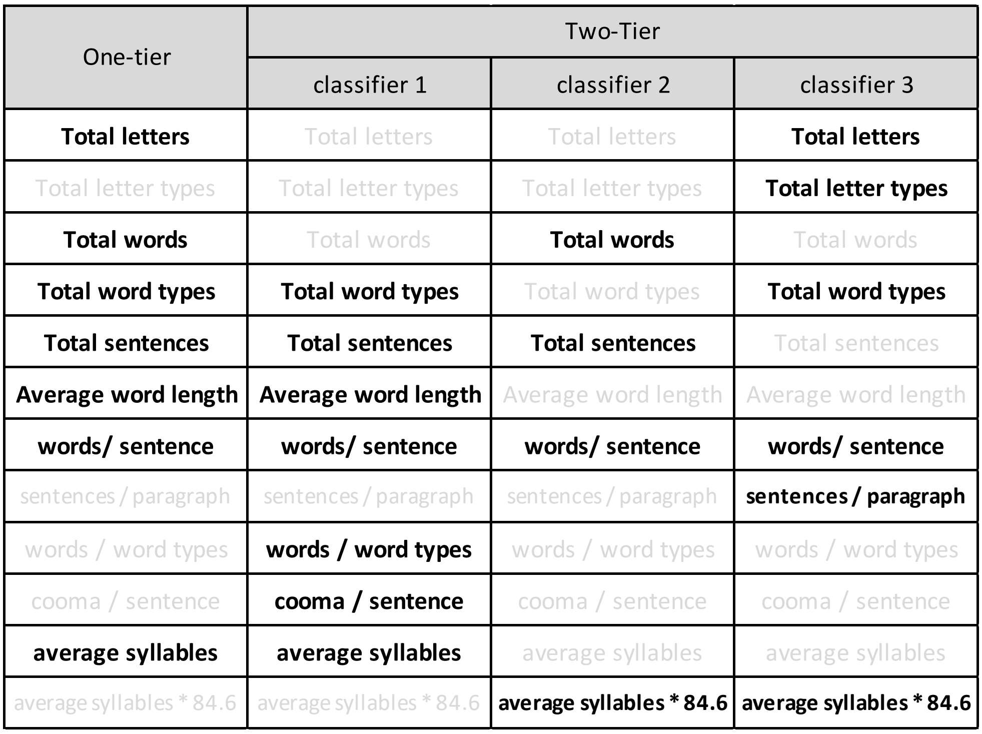
		Actual grades	
		J1 - J3	H1 - H3
Predicted grades	J1 - J3	60	4
	H1 - H3	3	43

Table 6.9 Result of the 2nd stage classification

		Actual grade					
		J1	J2	J3	H1	H2	H3
Predicted grade	J1	19	2	2	0	1	0
	J2	2	14	7	0	2	0
	J3	1	3	10	1	0	0
	H1	0	0	2	8	1	4
	H2	0	1	0	4	12	2
	H3	0	0	0	4	1	7

Table 6.10 Comparison of the result of experiment

classifier	accuracy (%)	F-measure
One-tier	59.091	0.575
1st / Two-tier	93.636	0.936
2nd / Two-tier	63.636	0.631



One-tier	Two-Tier		
	classifier 1	classifier 2	classifier 3
Total letters	Total letters	Total letters	**Total letters**
Total letter types	Total letter types	Total letter types	**Total letter types**
Total words	Total words	**Total words**	Total words
Total word types	**Total word types**	Total word types	**Total word types**
Total sentences	**Total sentences**	**Total sentences**	Total sentences
Average word length	**Average word length**	Average word length	Average word length
words/ sentence	**words/ sentence**	**words/ sentence**	**words/ sentence**
sentences / paragraph	sentences / paragraph	sentences / paragraph	**sentences / paragraph**
words / word types	**words / word types**	words / word types	words / word types
cooma / sentence	**cooma / sentence**	cooma / sentence	cooma / sentence
average syllables	**average syllables**	average syllables	average syllables
average syllables * 84.6	average syllables * 84.6	**average syllables * 84.6**	**average syllables * 84.6**

Figure 6.4 Comparison of feature subsets

6.4.3 Discussion

Similar to the previous experiment using textbooks from Japan, only the classifier 1 which classifies junior high and high school uses "comma per sentence" feature. This result suggests the number of comma used in sentence does not increase gradually but increase in phases.

6.5 Conclusions

In this study, a system which can classify English sentences according to difficulty level is developed by using meta-features of dataset in order to provide English learners with appropriate level of reading text and by applying following proposed methods:

- We propose a new method to set paragraph as a unit of analysis for one instance when building dataset. In order to find appropriate number of paragraphs for better classification, an experiment is run by making 5 datasets with a range of paragraphs from 5, 10, 15, 20 and 25. The result shows 20 paragraphs bears the highest accuracy. The proposed method also leads to more accurate classification compared to the existing study which employs page as a unit of analysis, showing the effectiveness of using the paragraph as a unit.

- Several experiments are conducted for various datasets by employing both one-tier and two-tier classifications. The results of the experiments show two-tier classification is more accurate than one-tier method. Also, first stage of two-tier classification shows considerably higher accuracy.

For a future research, following three points are worth exploring:

- Using 20 paragraphs as one incident produce higher accuracy in textbooks used in Finland. In order to develop a simpler and more versatile classification system, textbooks used in Japan and South Korea are converted into a dataset by using same paragraph numbers. However, due to linguistic and cultural differences, different paragraph numbers may produce higher classification accuracy in textbooks used in South Korea and Japan.
- Two features used for the study are both related to syllables. They are used widely in readability scores. However, these features have linear relations which can influence the result of the analysis. Although the charts comparing features selected in the study have shown the proposed system distinguish between two features, eliminating these linear relations can have certain changes in accuracy and feature selection.
- Several feature subsets are produced which allow more accurate classification. By analyzing these subsets, new findings can be obtained regarding how the sentences or structures would change in the process of the rise of difficulty level.

Chapter 7

Discriminant Analysis on University Students' Reading Skills

7.1 Introduction

The Courses of Study determined by the Ministry of Education, Culture, Sports, Science and Technology (MEXT) of Japan are broad standards for all schools, from kindergarten through high schools, to organize their programs in order to ensure a fixed standard of education throughout the country [1]. Since the end of World War II, the Course of Study have been revised 7 times, approximately at 10-year intervals. With the revisions, English education in Japan has gone through several reforms. The latest Courses of Study aim to nature communication skills in a foreign language [2 - 4].

The Course of Study does not apply to universities. However, a reform for university entrance examination has been implemented. In 2020, the current National Center Test will be replaced with the Common Test for University Admissions. In the new test system, applicants' English proficiency will be assessed in four skills (reading, listening, speaking and writing). In order to assess speaking and writing skills, a certificate exam will be used.

One of the certificate exams to be used is TOEIC. The test has been drawing attentions from business world, owing to the widening and acceleration of the economic globalization. A study conducted in 2013 to listed companies in Japan showed that 69% of respondents used TOEIC score in evaluating job applicants' qualification. The test was also used widely in deciding who to be promoted or transferred to overseas offices [5]. As a result, 2.5 million people took the test in 2017, of which 1.1 million were students [6].

In many private universities, the tests are used widely for entrance exam or credit certification. A survey conducted in December 2016 by the Institute for International Business Communication (IIBC), an administrator of the TOEIC in Japan, showed out of 751 universities surveyed, 427 used the test for entrance exam and 378 used the test for credit certification [7].

Although the test has been attracting as an objective certificate to assess examinee's proficiency, the cost is rather high. Depending on the test type, minimum of 5,000 JPY per test is necessary, making it harder to take one frequently. In an English course offered in a school, a workbook can be used for trial exam.

However, duplicating the workbook is prohibited by the copyright law. If students have to buy the workbook, preprocessing is necessary to hide answer keys included in the workbook.

When a student can estimate the TOEIC score from own learning outcomes related to course activities, it is possible for him or her to decide when to take an official test based on the estimated scores. The estimation will also allow a teacher to give necessary instruction and advice to each student according to his or her proficiency.

This study is a first step for the estimation of the score from the learning outcomes. The discriminant analysis has been applied to classify students into upper and lower groups based on TOEIC Bridge reading scores by using learning outcomes in an English course conducted in a public school in Ishikawa.

7.2. Existing studies

7.2.1 TOEIC Program

TOEIC is the abbreviation for Test Of English as International Communication and is developed by ETS, a non-profit educational foundation in the U.S. At the beginning, there was only one test type called TOEIC Listening and Reading (L&R). Later, a simplified test called TOEIC Bridge and a test to evaluate output performance called TOEIC Speaking and Writing (S&W) were developed. Table 7.1 shows score comparisons between TOEIC Bridge and TOEIC L&R.

Table 7.1 Score comparison: TOEIC Bridge and TOEIC L&R

Bridge	90	100	110	120	130	140	150	160
L&R	230	260	280	310	345	395	470	570

Source: IIBC

7.2.2 Estimation of TOEIC score

Taguchi [8] reports a correlation between TOEIC scores and self-study hours not related to the course based on data from students in Aichi University of Education. The study hours were self-reported in 6-point scale, so the reliability of the data is not sufficient.

There are many existing studies to estimate TOEIC scores from other certificate scores. Maruyama et al [9] have conducted an experiment to estimate TOEIC scores from G-TELP scores using a generalized linear model. Dohi and Cheung [10] estimate TOEC scores from TOEFL scores based on data of students in Chiba University by using a simple linear regression model. Eguchi [11] calculates a correlation between TOEIC scores and TOEFL scores based on data of students in Hokusei University. These existing studies reports interesting findings. However, each estimation requires scores from another certificate test, which requires additional cost.

This study aims to overcome the cost problem by using learning outcomes from course activities which do not require additional cost.

7.3. Experiment

7.3.1 Participants

First year students in the Faculty of Intercultural Communication of Komatsu University participated in this project. In fall semester of 2018, they were required to take "English III" course. Due to the physical size of the classroom, the course was divided into three classes held on Tuesdays, Wednesdays and Fridays. The students freely decided which class to register (Table 7.2).

Table 7.2 Course name, days and students registered

Class	Date	Male	Female	Total
English IIIa	Tue.13:00-	3	20	23
English IIIb	Wed.13:00-	12	12	24
English IIIc	Fri.13:00-	2	33	35
Total		17	65	82

76 students took TOEIC Bridge conducted in February of 2019. Three of them did not submit assignments for the course. Data from 73 students with both TOEIC Bridge and course assignments were used for discriminant analysis.

7.3.2 Textbook

“Skills for Better Reading, revised edition” published by Nanun-do was used for the course. According to the publisher, intended students for the text are expected to have TOEIC scores from 400 to 600. From Table 1, these scores can be interpreted as between 140 to 160 in TOEIC Bridge.

TOEIC Bridge is a simplified version of TOEIC. It consists of listening part (50 questions for 25 minutes) and reading part (50 questions for 35 minutes). The scores are 90 each (180 in total). Table 7.3 shows the test result conducted in February 2019. Compared to national average scores of first year university students (Total 124.0, Listening 61.1, Reading 62.9), the participating students have higher proficiency in reading and listening on average [6]. Since one of the course objectives was to improve reading skills, the reading scores were analyzed in this study.

Table 7.3 Descriptive statistics of TOEIC Bridge scores

	Total	Listening	Reading
Mean	149.29	72.30	76.99
SD	13.22	6.38	8.39
min	108	52	52
max	174	90	90
Median	152	72	80
skewness	-1.01	-0.45	-1.37

7.3.3 Learning outcomes

Assignments

The course was conducted over 16 weeks. For 13 weeks, reading assignments were given to the students. The assignments were adopted from written tests of EIKEN Grade P1 conducted and published by Eiken Foundation of Japan. A written test is composed of multiple-choice section (41 questions) and composition section (1 question). Out of 41 questions, 10 questions in reading sub-section were printed and distributed to the students as an assignment at the end of class each week. The sub-section is divided into three question sets, as shown in Table 7.4.

Table 7.4 Average words size for each question set.

	QS1	QS2	QS3	Total
Number of questions	3	3	4	10
Words in texts	312	412	494	1,218
Words in questions	241	239	343	823
Words in total	553	651	837	2,041

Note: QS: question set

According to Eiken Foundation's evaluation criteria, the intended examinees of the Grade P1 are second to third year university students. Successful examinees are expected to fully understand and use English required in actual social life situations. The level of the test is difficult for the participating students. For the copyrights of the past test, section1, article 35 of the copy rights law is applied for this project so that the tests can be reproduced without a permission from the copyright holder.

Mid-term and final exams

The mid-term exam was conducted in November 2018. The final exam was held in February 2019. The questions were made based on the textbook used in the course. The mid-term exam covered 6 units in the textbook and was conducted separately for each class. 50% of the questions were same among three classes and the remaining 50% were different among each class. The final exam covered 4 units of the textbook and was conducted all together. For the experiments, a weighted average score of mid-term and final exams was calculated for each student. Table 7.5 shows the statistical information and readability scores for each exam.

Table 7.5 Statistical information and readability scores for each exam

Exam	Class	Sent	Words	Syll	Lett	FKGL	ARI
Mid	A	65	860	1450	4432	9.5	9.5
	B	65	917	1529	4687	9.6	9.7
	C	70	961	1600	4862	9.4	9.3
Final	all	62	963	1558	4523	9.6	8.5

Note Sent: sentences, Syll: syllables, Lett: letters

There are many readability scores [12,13]. Flesch-Kincaid Grade Level (FKGL) is most widely used for assessing the appropriateness of a given textbook [14]. FKGL was developed by Flesch and Kincaid in 1975 and the number indicates an appropriate grade level in the U.S. school system for a document being analyzed. Ishioka et al [15] report English entrance tests in the National Center Test are at 4 to 8 in FKGL. Table 4 shows the exams for the course were more difficult than the entrance examination commonly used in Japan.

The formula of FKGL is as follows.

$FKGL = 0.39 * WPS + 11.8 * SyPW - 15.59$

where

WPS = Words Per Sentence

SyPW = Syllables Per Word

As the formula shows, information on syllables are required for each word to calculate FKGL. When there is a word in a text to be analyzed which does not have syllable information, FKGL cannot be calculated.

Automated Readability Index (ARI) was developed by U.S. Airforce and uses the number of letters to calculate the readability [16]. ARI was developed by U.S. Airforce. Its result shows the appropriate grade level, same as FKGL. The formula is as follows:

$ARI = 4.71 * LPW + 0.5 * WPS - 21.43$

where

LPW = Letters Per Word

WPS = Words Per Sentence

As shown in Table 7.5, except for the final exam's ARI, the readability scores did not show significant fluctuations. The result allowed to suppose all the students took same level of examinations.

Abbreviations in Table 7.6 are used in tables and figures for the remainder of the paper. Table 7.7 shows the learning outcome data.

Table 7.6 Legend

Abbreviation	Meaning
WAS	weighted average scores of mid and final exams
AAS	Assignment average scores
AHRS	Assignment study hours
ATMS	the number of submissions of assignment

Table 7.7 Descriptive statistics of learning outcome

	WAS	Assignment		
		AAS	AHRS	ATMS
Mean	71.17	5.15	1:11:15	10.77
SD	13.52	1.71	0:27:54	2.94
min	19.42	1.67	0:30:00	2
max	97.40	8.58	2:40:00	13
Median	73.15	5.18	1:05:50	12
Skewness	-0.97	-0.08	1.00	-1.75

7.3.4 Methods and Software

Google Apps were used for collecting and scoring the assignments. The students were required to register study hours in addition to the answers to the assignment. Bell Curve for Excel (version 2.15) from Social Survey Research Information was used for discriminant analysis. Mint Reading Grade Level Formulas from Mint Phonetics Education Institute was used to calculate readability scores for the mid-term and final exams.

We used discriminant analysis instead of regression analysis because the distribution of TOEIC Bridge reading score was not normal.

7.4. Results

7.4.1 Correlation

Data from 73 students were used to conduct discriminant analysis. The students were divided into upper and lower groups based on TOEIC Bridge reading scores. The threshold between the group was set at 80% correct scores. Explanatory variables were four learning outcomes listed in Table 7.6. The number of combinations of these 4 variables are 15. In order to simplify the analysis, the partial correlation coefficients were calculated to find a variable having a weak correlation with the reading score.

Table 7.8 and Fig.1.1 show that the number of submissions has a weak correlation with the reading score. This explanatory variable was excluded and the remaining three learning outcomes were used for discriminant analysis.

Table 7.8 Partial correlation matrix (n=73)

	1	2	3	4	5
1 Reading Score	-	.317	.332	-.276	-.056
2 WAS	**	-	.462	.001	-.027
3 AAS	**	**	-	-.073	.362
4 AHRS			**	-	.098
5 ATMS					-

Note: **,P<0.01, *,P<0.05

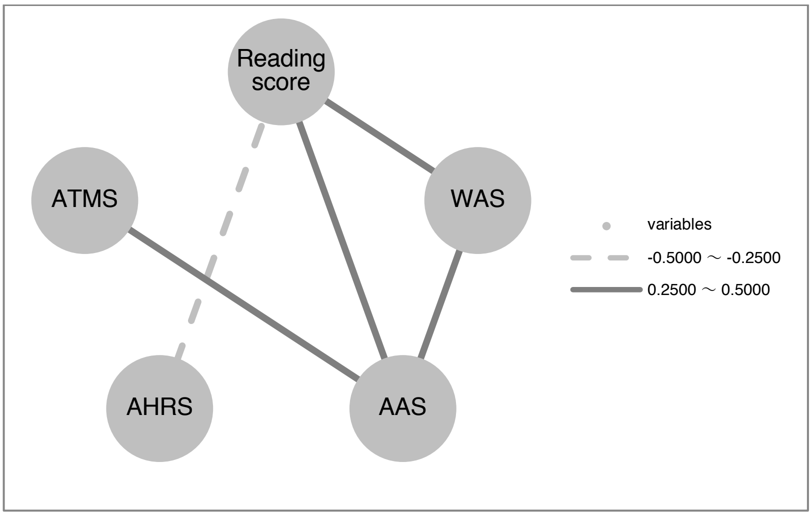


Fig.7.1 Undirected graph (P<0.05)

7.4.2 Overview of discriminant analysis

The analysis overview is shown in Table 7.9.

Table 7.9 Experiment results： percentage of correct classifications

model	Variable(s)	% of correct classifications		
		Upper	Lower	Total
1	a	85.00%	76.92%	83.56%
2	b	76.67%	84.62%	78.08%
3	c	81.67%	61.54%	78.08%
4	a×b	88.33%	92.31%	89.04%
5	a×c	88.33%	69.23%	84.93%
6	b×c	80.00%	84.62%	80.82%
7	a×b×c	88.33%	76.92%	86.30%

Note: a： WAS, b： AAS, c： AHRS

The value for upper group corresponds with recall, the lower group value corresponds with specificity, and the total value corresponds with accuracy. Discriminant analysis does not yield precision. The data from the experiment were applied to the formula for precision to yield F-value as shown in Table 7.10.

Table 7.10 Experiment results: precision and F-value

Model	Variable(s)	Precision		F-value	
		Upper	Lower	Upper	Lower
1	a	0.9444	0.5263	0.8947	0.6501
2	b	0.9583	0.4400	0.8519	0.5591
3	c	0.9074	0.4211	0.8596	0.5556
4	a×b	0.9814	0.6316	0.9298	0.7365
5	a×c	0.9298	0.5625	0.9060	0.6873
6	b×c	0.9600	0.4783	0.8727	0.5986
7	a×b×c	0.9464	0.5882	0.9138	0.7062

Note: a： WAS, b： AAS, c： AHRS

7.4.3 Detailed results for several models

Tables 7.11 and 7.12 respectively show the detailed results for models 4 and 6 which produced higher than 80% correct classification for both upper and lower groups.

Table 7.11 Experiment result of model 4

		Prediction		% of correct classification
		Upper	Lower	
Observation	Upper	53	7	88.33%
	Lower	1	12	92.31%
			Total	89.04%

Table 7.12 Experiment result of model 6

		Prediction		% of correct classification
		Upper	Lower	
Observation	Upper	48	12	80.00%
	Lower	2	11	84.62%
			Total	80.82%

Tables 7.13 and 7.14 respectively show the results for models 2 and 7, both with average assignment scores as an explanatory variable.

Table 7.13 Experiment result of model 2

		Prediction		% of correct classification
		Upper	Lower	
Observation	Upper	46	14	76.67%
	Lower	2	11	84.62%
			Total	78.08%

Table 7.14 Experiment result of model 7

		Prediction		% of correct classification
		Upper	Lower	
Observation	Upper	53	7	88.33%
	Lower	3	10	76.92%
			Total	86.30%

7.5. Discussion

7.5.1 Overview

As shown in Table 7.9, all the models except model 2 exceed 80% for correct classification for upper group. However, the correct classifications for lower group varies from 60% to 90 % among different models. As for precision, similar tendency can be observed from Table 7.10. Although precision for upper group exceed 0.9 in all the models, for lower group, the maximum is 0.6316 in model 4.

Incorrect classifications include actual lower group students being misclassified as upper group and vice versa. The former case will likely to occur when the difficulty levels of assignments and examinations are low. The latter case will likely to occur when these difficulties are high.

7.5.2 Model 2

This model is the only model with less than 80% correct classification for upper group classification. Approximately 25 % of the students who actually belong to upper group were predicted to be lower group students. This model employs only one variable (average assignment scores) for the prediction. The assignments were adopted from EIKEN Grade Pre-1 tests, which were at a higher difficulty level. The result suggests that even those who belong to upper group could not have higher score for the assignment.

7.5.3 Models 4 and 6

Models 4 and 6 have higher correct classifications for lower group than those of upper group. Both models employ average assignment scores for the prediction.

Model 4 uses weighted average scores of exams, too. These two explanatory variables allowed higher prediction not only for lower group but also for upper group.

Model 6 uses assignment study hours, in addition to average assignment scores. Compared to model 2, correct classification improves just by 3 % point for upper group and precision improves just in 0.03 point. As shown in Table 7.8, partial correlation coefficient between assignment study hours and assignment average scores was negative weak (-0.073), leading to lesser improvement in prediction for additional variable.

7.5.4 Model 7

The model uses all the explanatory variables. Compared to model 4 which does not use assignment study hours, accuracy and precision for lower group yield lower numbers. As shown in Table 7.8, the partial correlation between assignment study hours and reading score was statistically insignificant. This partly explains degrade in prediction.

7.6 Conclusions

Using certificate exam is effective to objectively evaluate proficiency. TOEIC has been attracting attention from business world. However, the cost to take test is one of the obstacles for students to take one regularly.

When prediction can be achieved through learning outcomes of English course, students can obtain necessary guideline for the preparation. Also, teachers can have valuable index for class management.

In this study, discriminant analysis was applied in order to predict upper and lower group of TOEIC Bridge reading scores from learning outcomes. The results showed that a model employing weighted average exam scores and average assignment scores predicted upper and lower group with 89.04% of accuracy. However, for the lower group, the precision was lower, suggesting assignments with higher difficult level misclassified upper group students as lower group students. In order to predict students' proficiency accurately, assignments whose difficulty levels are calibrated properly according to students' skill are important. Through these calibrated assignments, students will have a higher chance to improve their reading skills which, in turn, will have a positive influence on the result of a certificate exam.

There are three directions for future study.

The first direction of the study is to expand the participating students to include different faculties in order to find a better model in predicting students' reading proficiency. One of the authors is scheduled to teach technical English for students in a faculty of science. The new experiments and results by applying this method to the students will be useful for many professors in similar faculties to review overall English course structures.

The second direction of the study is a further analysis of study hours. Discussions in 5.3 and 5.4 suggest that although many upper group students spent shorter hours for the assignments, some used longer hours. Analyzing factors influencing the difference in study hours among the upper group students will lead to a new finding for more effective classification criteria.

And the third direction is to incorporate ability scores provided by TOEIC operator to improve accuracy of discriminant analysis. For TOEIC Bridge used in this study, five sub-scores are provided. Since each sub-score is rated from one to three and no distinctions are made between listening and reading sections, they are not good input for the analysis. However, TOEIC L&R test result comes with ten ability scores, five each for listening and reading sections. Each score is evaluated in percentile. The distinction between listening and reading section and percentile evaluation make these abilities scores good candidate for future analysis.

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Chapter 8

Conclusions

The purpose of this study is to develop a system which estimates difficulty level of English sentences. School textbooks used in three countries (Finland, Japan, South Korea) were used in the experiments to investigate the effectiveness of the proposed classification system which has two-tier classifiers.

The system has been developed by using textbook data from Finland. However, the results have showed the experiments using textbooks used in Japan yielded the highest F-value (0.750), followed by those used in South Korea (0.631). F-value for the experiment using textbooks for seven years in Finland showed the lowest result (0.609). These results can be interpreted that the textbooks used in Japan and South Korea have fewer overlap between grades compared to those used in Finland, especially for junior high school.

Despite these differences in F-value for the experiment results, the proposed system has shown overall high accuracy especially at the first stage. General classification by the first-stage classifier offers good starting point to many English learners to find a reading material which suits reading skills for each learner. Reading materials classified as equivalent to junior high textbooks can be recommended to most of the learner, since compulsory education continues until junior high and by definition, almost all the people in Japan are expected to understand English text at this level.

This system can be used also for university students whose achievement in course work or certificate exams are below average. These students are on average have insufficient reading activities, which result in slow paced reading and/or inaccurate interpretation of the texts. In order to tackle these shortcomings, each student should be able to find reading materials appropriate for their reading skills. By using the proposed system, they should be able to find suitable reading materials for them to enjoy, leading to enhancement of their reading skills.

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