Combining Prediction by Partial Matching and Logistic Regression for Thai Word Segmentation

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Abstract

Word segmentation is an important part of many applications, including information retrieval, information filtering, document analysis, and text summarization. In Thai language, the process is complicated since words are written continuously, and their structures are not well-defined. A recognized effective approach to word segmentation is Longest Matching, a method based on dictionary. Nevertheless, this method suffers from character-level and syllable-level ambiguities in determining word boundaries. This paper proposes a technique to Thai word segmentation using a two-step approach. First, text is segmented, using an application of Prediction by Partial Matching, into syllables whose structures are more well-defined. This reduces the earlier type of ambiguity. Then, the syllables are combined into words by an application of a syllable-level longest matching method together with a logistic regression model which takes into account contextual information. The experimental results show the syllable segmentation accuracy of more than 96.65% and the overall word segmentation accuracy of 97%.

1 Introduction

In Thai language, characters are written without explicit word boundaries. Depending on the contexts, there can be many ways to break a string into words, for instance, "อาจอง" can be segmented as "อา*อาจ" or "อาจ*อง", and "นั่งตากลม" can be segmented as "นั่ง*ตากลม" or "นั่ง*ตาก*ลม". This complicates the task of identifying word boundaries.

Longest matching is the most popular approach to Thai word segmentation (Pooworawan, 1986). The algorithm scans text from left to right and selects the longest match with a dictionary entry at each point, in a greedy fashion. However, longest possible words may not comply with the actual

meanings. For example, "ชาวบ้านรอกทราบพระ" is segmented by the longest matching as "ชาวบ้าน-รอก-ทราบ-พระ" instead of the correct segmentation "ชาวบ้าน-รอก-ทราบ-พระ". This type of ambiguity is referred to as character-level ambiguity. In addition, "เขารับรองเท้าจากเพื่อน" is segmented as "เขา-รับ-รอง-เท้า-จาก-เพื่อน" instead of the correct segmentation "เขา-รับ-รอง-เท้า-จาก-เพื่อน". This is referred to as syllable-level ambiguity.

The technique we propose is a two-step process to word segmentation. In the first step, text is segmented into a sequence of syllables, whose structures are more well-defined. This reduces the character-level ambiguity. The remaining syllable-level ambiguity is the task of combining those syllables into words.

2 Related Work

In addition to the longest matching algorithm, discussed earlier, the maximum matching algorithm (Sornlertlamvanich, 1993) was proposed to get around the greedy characteristic of the longest matching algorithm by generating all possible segmentations for a sentence and then selecting the one which contains the fewest number of entries in the dictionary.

An application of statistical techniques was proposed by (Pornprasertkul, 1994), using a Viterbi-based approach to exploit statistical information derived from grammatical tags. Later, (Kawtrakul and Chalathip, 1995) and (Meknawin *et al.*, 1997) used variants of the trigram model to compute the most likely segmentation. (Theeramunkong and Sornlertlamvanich, 2000) observed that, in Thai language, some contiguous characters tend to be inseparable units, called Thai character cluster (TCC), and proposed a set of rules to group characters into TCCs for the purpose of text retrieval.

3 Syllable Segmentation

Prediction by Partial Matching (PPM) (Bell *et al.*, 1990; Cleary and Witten, 1984), a symbolwise compression scheme, is used to build the model for Thai text. PPM generates a prediction for each

input symbol based on its previous context (i.e., a few, say k , foregoing symbols in the text). The prediction is encoded in form of conditional probability, conditioned on the preceding context. PPM maintains predictions, computed from the training data, for the largest context (k) as well as all shorter contexts in tables, as shown in Table 2.

	Type	Symbol	Character
1	Middle consonant	m	กจดจฎญป
2	High consonant	h	ขฉฐดฬฝศษส
3	Single lower consonant	s	งญณบมยรลวฬ
4	Double lower consonant	d	คณชนจลลททฬทฬซ
5	Front vowel1	f	ิ ี ใ ื
6	Front vowel 2	a	เ
7	Upper vowel1	u	อ ๑ ๒ ๓ ๔
8	Upper vowel2	p	๕ ๖
9	Rear vowel1	r	า
10	Rear vowel2	e	ำ ๗ ๘ ๙
11	Lower vowel	l	๑ ๒
12	Garun	g	๑
13	Tonal	t	๑ ๒ ๓ ๔ ๕ ๖ ๗ ๘ ๙
14	Rue	z	ฤ ฦ
15	O-Ang	o	๑
16	Separator	*	white space

We illustrate the insertion of spaces between characters using text "จ้ำนกั๋ญ". In Thai, tonals are not useful for the segmentation purpose, thus are first filtered out, and the text is converted to "de*fs*mu*hl".

In order to predict the next symbol, the algorithm follows the concept of PPM by attempting to find first the context of length k ($k = 2$ in this example) for this symbol in the context table (i.e., $e^* \rightarrow f$). If the context is not found, it passes the probability of the escape character at this level and goes down one level to the $(k-1)$ context table to find the current context of length $k-1$ (i.e., $* \rightarrow f$). The process is repeated until a context is found. If it continues to fail to find a context, it may go down ultimately to order (-1) corresponding to equiprobable level for which the probability of any next character is $1/|A|$, where A is the number of distinct characters.

To handle zero frequency, we use method D (PPMD) (Witten and Bell, 1991) where the escape character gets a probability of $(d/2n)$, and the symbol gets a probability of $(2c-1)/2n$ where n is the total number of symbols seen previously, d is the total number of distinct contexts, and c is the total number of contexts that appear in the string.

order 2					order 1						
		e	n	p			e	n	p		
de	-->	*	1	1	0.5	d	-->	e	1	2	0.25
	-->	esc	1	1	0.5		-->	p	1	2	0.25
zd	-->	p	1	1	0.5		-->	esc	2	2	0.5
	-->	esc	1	1	0.5	z	-->	d	1	1	0.5
dp	-->	s	1	1	0.5		-->	esc	1	1	0.5
	-->	esc	1	1	0.5	p	-->	s	1	1	0.5
hl	-->	*	1	1	0.5		-->	esc	1	1	0.5
	-->	esc	1	1	0.5	m	-->	u	1	1	0.5
as	-->	h	1	1	0.5		-->	esc	1	1	0.5
	-->	esc	1	1	0.5	u	-->	*	1	2	0.25
sh	-->	g	1	1	0.5		-->	s	1	2	0.25
	-->	esc	1	1	0.5		-->	esc	2	2	0.5
hs	-->	u	1	1	0.5	l	-->	*	1	1	0.5
	-->	esc	1	1	0.5		-->	esc	1	1	0.5
su	-->	s	1	1	0.5	a	-->	s	1	3	0.166667
	-->	esc	1	1	0.5		-->	h	1	3	0.166667
us	-->	s	1	1	0.5		-->	o	1	3	0.166667
	-->	esc	1	1	0.5		-->	esc	3	3	0.5
ss	-->	*	1	1	0.5	h	-->	g	1	3	0.166667
	-->	esc	1	1	0.5		-->	s	1	3	0.166667
ao	-->	r	1	1	0.5		-->	l	1	3	0.166667
	-->	esc	1	1	0.5		-->	esc	3	3	0.5
or	-->	*	1	1	0.5	s	-->	s	1	6	0.08333333
	-->	esc	1	1	0.5		-->	h	1	6	0.08333333
fs	-->	*	1	1	0.5		-->	u	1	6	0.08333333
	-->	esc	1	1	0.5		-->	*	3	6	0.416667
ps	-->	*	1	1	0.5		-->	esc	4	6	0.333333
	-->	esc	1	1	0.5	e	-->	*	1	1	0.5
mu	-->	*	1	1	0.5		-->	esc	1	1	0.5
	-->	esc	1	1	0.5	g	-->	*	1	1	0.5
ah	-->	s	1	1	0.5		-->	esc	1	1	0.5
	-->	esc	1	1	0.5	o	-->	r	1	1	0.5
hg	-->	*	1	1	0.5		-->	esc	1	1	0.5
	-->	esc	1	1	0.5	r	-->	*	1	1	0.5
s*	-->	a	1	2	0.25		-->	esc	1	1	0.5
	-->	m	1	2	0.25	f	-->	s	1	1	0.5
	-->	esc	2	2	0.5		-->	esc	1	1	0.5
r*	-->	f	1	1	0.5	*	-->	f	1	7	0.0714286
	-->	esc	1	1	0.5		-->	h	1	7	0.0714286
u*	-->	h	1	1	0.5		-->	m	1	7	0.0714286
	-->	esc	1	1	0.5		-->	a	3	7	0.357143
l*	-->	a	1	1	0.5		-->	z	1	7	0.0714286
	-->	esc	1	1	0.5		-->	esc	5	7	0.357143
g*	-->	a	1	1	0.5	order 0					
	-->	esc	1	1	0.5			e		n	p
e*	-->	z	1	1	0.5	-->	d	2	33	0.0454545	
	-->	esc	1	1	0.5	-->	e	1	33	0.0151515	
*a	-->	o	1	3	0.166667	-->	*	8	33	0.227273	
	-->	s	1	3	0.166667	-->	z	1	33	0.0151515	
	-->	h	1	3	0.166667	-->	p	1	33	0.0151515	
	-->	esc	3	3	0.5	-->	s	6	33	0.166667	
*m	-->	u	1	1	0.5	-->	m	1	33	0.0151515	
	-->	esc	1	1	0.5	-->	u	2	33	0.0454545	
*h	-->	l	1	1	0.5	-->	h	3	33	0.0757576	
	-->	esc	1	1	0.5	-->	l	1	33	0.0151515	
*f	-->	s	1	1	0.5	-->	a	3	33	0.0757576	
	-->	esc	1	1	0.5	-->	g	1	33	0.0151515	
*z	-->	d	1	1	0.5	-->	o	1	33	0.0151515	
	-->	esc	1	1	0.5	-->	r	1	33	0.0151515	
						-->	f	1	33	0.0151515	
						-->	esc	15	33	0.227273	
order - 1											
1 / A

To improve the efficiency of the algorithm, the structure can be pruned by the following set of rules, generated from the language analysis:

The nodes surrounded by a rectangle in Figure 1 are pruned according to the rules above. Thus, they do not generate further subtrees.

In this section, we propose a technique to form words by combining syllables together. In order to combine syllables into words, for each sentence we first locate ambiguous sequences of syllables, i.e., syllable sequences that can be combined in many ways. The forward and backward syllable-level longest matching are performed. These algorithms are modified from the original longest matching, described in Section 1, by considering syllable as a unit, instead of character. For instance, a syllable sequence "รายงาน*เป็น*ต้น*ฉบับ" is processed according to the forward longest matching as "รายงาน*เป็นต้น*ฉบับ", while as "รายงาน*เป็นต้น*ฉบับ" according

to the backward longest matching. The inconsistencies between the two algorithms suggest ambiguous sequences of syllables in the sentence. In this example, an ambiguous sequence of syllables is "เป็น*ค้น*ฉบับ".

After identifying ambiguous syllable sequences, we perform the following steps:

Step 1: Between the results of the forward and backward longest matching, the one with all words appearing in the dictionary is selected as the result of the ambiguous sequence. If both results satisfy this condition, go to Step 2.

Step 2: The result with the least number of words is taken as the answer. If the number of words are equal, go to Step 3.

Step 3: A logistic regression model for combining syllables is consulted. This step will be discussed in details below.

	Sylla- ble 1	Sylla- ble 2	Sylla- ble 3	Sylla- ble 4	Merge (Y/N)
1	เขา	รับ	รอง	เท้า	N
2	รับ	รอง	เท้า	จาก	Y
3	รอง	เท้า	จาก	เพื่อน	N

Table 3: Syllable Organization for the Logistic Regression Model

4.1 Logistic Regression Model for Combining Syllables

The model to combine syllables is built upon Binary Logistic Regression whose answers are either combine or not combine. The model considers four consecutive syllables at a time when modeling the decision of whether to combine the middle two syllables together. The first and the fourth syllables are considered the context of the two middle ones. Table 3 shows the organization of data for the model. In the first row, the training data specifies that syllables "รับ" and "รอง" (with the preceding contextual syllable "เขา" and the following contextual syllable "เท้า") should not be combined. The model is trained by every row of the training data. The result is a trained logistic regression model that can be used for guiding whether the middle two syllables should be combined in the context of the surrounding syllables (the first and the fourth syllables).

In the model, each syllable (in Table 3) is represented by a set of features. The syllables under consideration (the second and the third syllables) are represented by 65 features, listed in Table 4.

The contextual syllables (the first and the fourth) are represented by a fewer number of features to

make it less specific to the training contexts. The variables for contextual syllables are those statistically significant to the prediction, returned with the regression. The final set consists of 35 variables, as shown in Table 5. The value of each variable is either 1 or -1 which means either the syllable contains or does not contain that particular character, respectively.

Var#	Char	Var#	Char	Var#	Char
1	ก	23	น	45	๖
2	ข	24	บ	46	๗
3	ค	25	ป	47	๘
4	ฅ	26	ผ	48	๙
5	ง	27	ฝ	49	๐
6	จ	28	พ	50	๑
7	ฉ	29	ฟ	51	๒
8	ช	30	ภ	52	๓
9	ซ	31	ม	53	๔
10	ด	32	ย	54	๕
11	ฎ	33	ร	55	๖
12	ฏ	34	ล	56	๗
13	ฏ	35	ว	57	๘
14	ฐ	36	ศ	58	๙
15	ฑ	37	ษ	59	๐
16	ฒ	38	ส	60	๑
17	ณ	39	ห	61	๒
18	ด	40	อ	62	๓
19	ต	41	พ	63	๔
20	ถ	42	ธ	64	๕
21	ท	43	ฤ	65	๖
22	ธ	44	ฦ		

Table 4: Syllable Representation for the Second and Third Syllables

5 Experimental Evaluation

In the first experiment, we evaluate the proposed syllable segmentation method. The algorithm is trained with 2,200 syllables, manually segmented from a dictionary. The test data used is a text excerpt from a thesis written in Thai. The results in Table 6 show that the algorithm at order 4 yields the best result which is, from the 1,714 manually segmented syllables, the algorithm correctly identifies 1,694 (or 98.83%) of them correctly. Figure 2 shows an example of segmentation results.

Var#	Char	Var#	Char	Var#	Char
1	ข	13	ส	25	ไ
2	ง	14	อ	26	ำ
3	จ	15	ะ	27	ู
4	ญ	16	า	28	เ
5	ฎ	17	ะ	29	ะ
6	ฑ	18	า	30	ะ
7	บ	19	ะ	31	ะ
8	ป	20	ะ	32	ะ
9	พ	21	ะ	33	ะ
10	ฟ	22	ะ	34	ะ
11	ย	23	ะ	35	ะ
12	ว	24	ะ		

Table 5: Syllable Representation for the First and Fourth Syllables

Order	Accuracy
1	77.36%
2	96.38%
3	98.54%
4	98.83%
5	98.19%

Table 6: Results of the PPM Model at Different Orders

Next, we evaluate the proposed algorithm at order 4 against five 1,000-syllable test texts which are not part of the text used in the training. The results in Table 7 show 96.65 to 98.26% segmentation accuracy.

Order	Accuracy
1	77.36%
2	96.38%
3	98.54%
4	98.83%
5	98.19%

Table 7: Results of Five 1,000-Syllable Texts

To evaluate the syllable combination technique, we create 50 ambiguous test cases. The results show that 47 cases (94%) are segmented correctly using the technique proposed, in which 13 cases are correctly segmented in Step 1; 11 cases are correctly segmented in Step 2, and 23 cases are correctly segmented in Step 3.

An evaluation of the entire process of word segmentation (i.e., from syllable segmentation to syllable combination) shows an accuracy of 97.17% by which 76.92% of those incorrect

segmentation roots from incorrect syllable segmentation.

Example Text	Syllable Segmentation Result
บัญชีแยกประเภททั่วไป ประกอบด้วยบัญชีประเภท ต่างๆ คือสินทรัพย์ หนี้สิน ส่วนของเจ้าของ รายได้ และ ค่าใช้จ่าย ซึ่งจะนำไปทำงบ ทดลอง ถ้ากิจการใช้บัญชีย่อย ประกอบบัญชีคุมยอด เฉพาะ บัญชีคุมยอดเท่านั้นจึงจะ ปรากฏในบัญชีแยก ประเภท ทั่วไป เนื่องจากวัตถุประสงค์ ขั้นสุดท้ายของการทำบัญชี แยกประเภททั่วไปก็คือ ให้ข้อ มูลที่เพียงพอในการจัดทำงบ การเงิน ดังนั้นในการจัดตั้ง บัญชีของกิจการใดก็ตามควร คำนึงถึงความต้องการของฝ่าย จัดการ เกี่ยวกับข้อมูลที่ต้อง ใช้เพื่อการตัดสินใจ	บัญชี*แยก*ประ*เภท*ทั่ว*ไป* ประ*กอบ*ด้วย*บัญชี*ประ*เภท* ต่าง*ๆ*คือ*สิน*ทรัพย์*หนี้*สิน* ส่วน*ของ*เจ้า*ของ*ราย*ได้*และ* ค่า*ใช้*จ่าย*ซึ่ง*จะ*นำ*ไป*ทำ* งบ*ทดลอง*ถ้า*กั*การ*ใช้*บัญชี* ประ*กอบ*บัญชี*คุม*ยอด* เฉพาะ* บัญชี*คุม*ยอด*เท่านั้น*จึง*จะ* ปรากฏ*ใน*บัญชี*แยก*ประ*เภท* ทั่ว*ไป* เนื่องจาก*วัตถุประสงค์* ขั้น*สุด*ท้าย*ของ*การ*ทำ*บัญชี* แยก*ประ*เภท*ทั่ว*ไป*ก็*คือ* ให้*ข้อ* มูล*ที่*เพียงพอ*ใน*การ*จัดทำ*งบ* การ*เงิน* ดังนั้น*ใน*การ*จัด*ตั้ง* บัญชี*ของ*กิจการ*ใด*ก็*ตาม*ควร* คำนึง*ถึง*ความ*ต้องการ*ของ*ฝ่าย* จัดการ* เกี่ยวกับ*ข้อมูล*ที่*ต้อง* ใช้*เพื่อ*การ*ตัดสินใจ

Figure 2: An Example of Syllable Segmentation

Lastly, we use the same test data however with correctly identified syllables, the performance shows 99.35% accuracy. This emphasizes the importance of pre-segmenting syllables and at the same time indicates that the proposed syllable combining method is effective.

6 Conclusion

This paper proposes a two-step approach to Thai word segmentation. Studying the characteristics of Thai language, we find that word segmentation possesses ambiguities at both character and syllable levels. The proposed technique consists of two steps. The first step is designed to reduce the character-level ambiguity by focusing on extracting syllables whose structures are more well-defined. Then the second step combines syllables into words by using binary logistic regression model. Experimental evaluations emphasize the importance of pre-identifying syllables correctly, show the accuracy of applying PPM to syllable segmentation of 98%, and indicate the effectiveness of the proposed approach to combine syllables into words. The overall accuracy of Thai word segmentation is 97.17%.

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