IJCLA VOL. 1, NO. 1-2, JAN-DEC 2010, PP. 61-83
RECEIVED 12/12/09 ACCEPTED 16/01/10 FINAL 08/03/10

Thai Rhetorical Structure Tree Construction

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ABSTRACT

A rhetorical structure tree (RS tree) is a representation of elementary discourse units (EDUs) and discourse relations among them. An RS tree is very useful to many text processing tasks utilizing relations among EDUs such as text understanding, summarization, and question-answering. Thai language with its distinctive linguistic characteristics requires a unique RS tree construction technique. This article proposes an approach to Thai RS tree construction; it consists of two major steps: EDU segmentation and RS tree construction. Two hidden Markov models constructed from grammatical rules are employed to segment EDUs, and a clustering technique with its similarity measure derived from Thai semantic rules is used to construct a Thai RS tree. The proposed technique is evaluated using three Thai corpora. The results show the Thai RS tree construction effectiveness of 94.90%.

Keywords: Thai Language, Elementary Discourse Unit, Rhetorical Structure Tree.

1 INTRODUCTION

A rhetorical tree (RS tree) is a tree-like representation of elementary discourse units (EDUs) and discourse relations (DRs) among them. It can be defined as: RS tree = (status, DR, promotion, left, right) where status is a set of EDUs; DR is a set of discourse relations; promotion is a subset

of EDUs; and left and right can either be NULL or recursively defined objects of type RS tree [14, 16].

Definition of EDU may vary. Some researchers consider an EDU to be a clause or a clause-like [16] excerpt while others consider them to be a sentence [18] in discourse parsing. A number of techniques are proposed to determine EDU boundaries for English language such as those using discourse cues [1, 6, 15], punctuation marks [6, 16], and syntactic information [16, 18, 19].

Many discourse relations can be used in writings. Some have a single nucleus such as elaboration and condition while others have multiple nucleuses such as contrast [13]. A number of techniques for determining relations between EDUs are proposed, such as those using verb semantics [20] to build verb-based events, using cue phrases/discourse markers (e.g., “because”, “however”) [15], and using machine learning techniques [16].

Chaniak [5] constructs RS trees by using statistical techniques, taking into account part-of-speech tagging on syntax, and using a corpus like the Penn tree-bank [20] to produce statistical RS trees. Statistical RS Trees work by assigning probabilities to possible RS trees of sentences. The probability of an entire RS tree is the product of the probabilities for each of the rules used therein.

Ito, *et.al.* [10] construct RS trees by using linguistic clues and rules to identify relation types, i.e., clausal-sequence, conjunction, means and circumstance, and using features of subject and verb in the clauses to predicate adjacent child units of the relations.

For Thai language, Sukvaree, *et.al.* [21] purpose a technique to construct an RS tree by using global and local spanning trees which makes decisions by discourse markers.

This article proposes a new approach to Thai RS Tree construction which consists of two major steps: EDU segmentation and RS tree construction. Two Hidden Markov models constructed from syntactic properties of Thai language are used to segment EDUs, and a clustering technique with its similarity measure derived from semantic properties of Thai language is then used to construct a Thai RS tree.

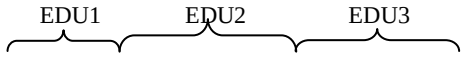
2 ISSUES IN THAI RS TREE CONSTRUCTION

Thai language has unique characteristics both syntactically and semantically. This makes techniques proposed for other languages not

directly applicable to Thai language. A number of important issues with respect to constructions of Thai RS trees are discussed in this section.

2.1 No Explicit EDU Boundaries

Unlike English, Thai language has no punctuation marks (e.g., comma, full stop, semi-colon, and blank) to determine the boundaries of EDUs. Therefore, EDU segmentation in Thai language becomes a nontrivial issue.



Thai : [w1w2…wmwm+1wm+2…wnwn+1wn+2…wo]
English : [w1 w2 … wm],[wm+1 wm+2 … wn];[wn+1 wn+2 … wo].
Where w_i is a word in text.

2.2 EDU Constituent Omissions

Given two EDUs, an absence of subject, object or conjunction in the anaphoric EDU may happen, such as a situation where an anaphoric EDU omits the subject that refers back to the object of the cataphoric EDU. Accordingly, EDU boundaries are ambiguous.

Thai text :	“เพื่อนจะขอยืมหนังสือ เพราะหาซื้อไม่ได้” (A friend’s going to borrow this book because she hasn’t been able to find it.)
Three possibilities :	1) [S(เพื่อน)V(จะขอยืม)O(หนังสือ)]$_{EDU1}$ [because S(Φ) V(หาซื้อไม่ได้)]$_{EDU2}$
	2) [S(เพื่อน)V(จะขอยืม)O(หนังสือ)]$_{EDU1}$ [because(Φ)S(Φ)V(หาซื้อไม่ได้)]$_{EDU2}$
	3) [S(เพื่อน)V(จะขอยืม)O(Φ)]$_{EDU1}$ [because(Φ)S(หนังสือ)V(หาซื้อไม่ได้)]$_{EDU2}$

In addition, the absence of subject, object or preposition which is a modifier nucleus of VP especially in the anaphoric EDU makes the use of word co-occurrence alone not sufficient to determine the relation between EDU1 and EDU2. For example,

EDU1: ศาลได้มีคำสั่งให้แยกสินสมรส (A court has ordered partition of marriage properties.)

EDU2: Φ1 จะสั่งยกเลิกการแยก Φ2 ได้ (Φ1 can cancel the partition of Φ2.)

In the example, EDU2 omits subject “ศาล” (court) and object ‘สินสมรส’ (marriage properties). Therefore, word co-occurrence alone is not sufficient to determine this relation.

2.3 Implicit Markers

The absences of discourse markers in Thai language are often occurred. In the example below, “แต่” (but) is a discourse marker which is omitted, but the relation between EDU1 and EDU2 is still able to determine.

EDU1: ศาลได้มีคำสั่งให้แยกสินสมรส (A court has ordered partition of marriage property.)
EDU2: Φ ภริยาหรือสามีคัดค้าน (Φ a wife or a husband may contest.)

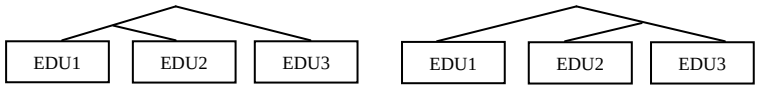
Therefore, considering markers or cue phrases alone is not sufficient to determine the relation between EDUs.

2.4 Adjacent Markers

Given three EDUs with two markers, as shown in the example below, two RS Trees are possible.

EDU1: ศาลได้มีคำสั่งให้แยกสินสมรส (A court has ordered partition of marriage properties.)
EDU2: แต่ถ้าภริยาหรือสามีคัดค้าน (but if a wife or a husband contests,)
EDU3: ศาลจะสั่งยกเลิกการแยกได้ (the court can cancel the partition.)

The first possibility, EDU1 and EDU2 relate first by a discourse marker “แต่” (but), next (EDU1, EDU2) and EDU3 relate by a marker “ถ้า” (if). For the other possibility, EDU2 and EDU3 relate first by a marker “ถ้า” (if), next that between (EDU2, EDU3) and EDU1 relate by a marker “แต่” (but).



a) The RS tree with “but” applied first b) The RS tree with “if” applied first

Fig. 1. Adjacent markers issue

3 STRUCTURES OF THAI EDUS

A Thai EDU consists of infrastructure and adjunct constituents. The twelve possible arrangements of Thai EDUs [17] are shown in Table 1. The structure of an EDU "A teacher usually doesn't drink alcohol" is shown in Fig. 2.

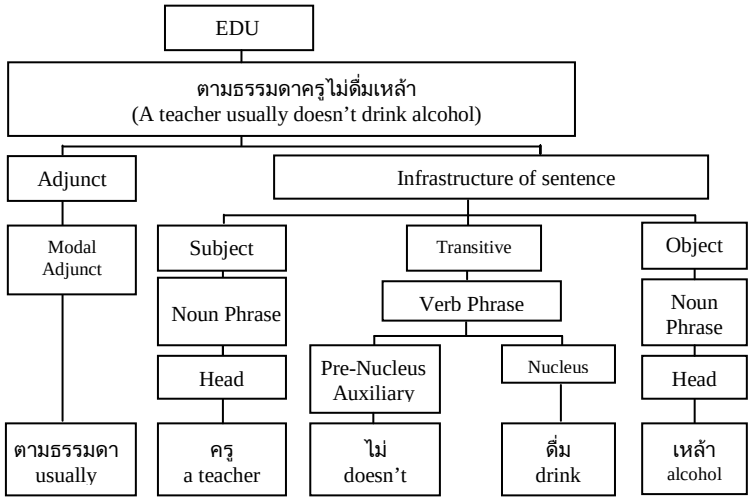


Fig. 2. Structure of the EDU "A teacher usually doesn't drink alcohol."

4 EDU SEGMENTATION

This section describes the EDU segmentation technique proposed in this research. To reduce the segmentation ambiguities caused from omissions of words or discourse markers, and the appearances of modifiers, noun phrases and verb phrases which are constituents of EDUs are first determined, according to the syntactic properties of Thai language. These phrases are then used to identify boundaries of EDUs.

Table 1: The possible arrangements of Thai EDUs.

EDUs	**Examples**	**Rules**
Vi	หิว (I'm hungry.)	NP_S-*Vi*-NP_S
S-Vi	ฝน-ตก (It's rain.)	

Vi-S	เจ็บไหม-คุณ (Are you pain?)	
Vt-O	หิว- น้ำ (I'm hungry.)	NP_O-NP_S-*Vt*-NP_O
S-Vt-O	รถ-ชน-เด็ก (The car hit the boy.)	
O-S-Vt	รูปนี้-ฉัน-ดูแล้วละจ๊ะ (I've already seen this photograph.)	
Vtt-O-I	ยังไม่ได้ให้-ยา-คนไข้ (I haven't given the patient the medicine.)	NP_S-*Vtt*-NP_O-NP_I
S-Vtt-O-I	ใคร-ให้-ลูกกวาด-หนู (Who gave you the sweet?)	
O-S-Vtt-I	ความลับ-ใครละ-จะกล้าถาม- คุณ (Who would dare to ask you the secret?)	NP_O-NP_S-*Vtt*-NP_I
I-S-Vtt-O	หนู-ป้า-จะให้-บ้านนี้ (Niece, I am going to give you this house.)	NP_I-NP_S-*Vtt*-NP_O
N	ป้า (Auntie)	NP_N-NP_N
N-N	นี่ปากกา-ใคร (Whose pen is this?)	
N-N	นี่ปากกา-ใคร (Whose pen is this?)	

A noun phrase (NP) is a noun or a pronoun and its expansions which may function as one of the four Thai EDU constituents, namely subject (S), object (O), indirect object (Oi) and nomen (N). The general structure of a noun phrase consists of five constituents which are: head (H), intransitive modifier (Mi), adjunctive modifier (Ma), quantifier (Q), and determinative (D).

A verb phrase (VP) is a verb and its expansions which may function as one of the three Thai EDU constituents, namely intransitive verb (Vi), transitive verb (Vt) and double transitive verb (Vtt). The general structure of a verb phrase consists of four constituents which are: nucleus (Nuc), pre-nuclear auxiliary (Aux1), post-nuclear auxiliary (Aux2), and modifier (M).

There are twenty five possible arrangements of noun phrase and ten arrangements of verb phrases [17], which are shown in Table 2.

4.1 Phrase Identification

To perform phrase identification, word segmentation and part of speech (POS) tagging are performed using SWATH [7] which extracts words and classifies them into 44 types such as common noun (NCMN), active verb (VACT), personal pronoun (PPRS), definite determiner

(DDAC), unit classifier (CNIT) and negate (NEG). A hidden Markov model (HMM) [11] employs these POS tag categories to determine phrases. The model assumes that at time step *t* the system is in a hidden state *PC(t)* which has a probability b_{jk} of emitting a particular visible state of POS tag *tag(t)*, and a transition probability between hidden states a_{ij}:

$$a_{ij} = p(PC_j(t+1)|PC_i(t)). \quad (1)$$

$$b_{jk} = p(tag_k(t)|PC_j(t)). \quad (2)$$

where *PC(t)* is the phrase constituent at time step *t*, and *tag(t)* is POS tag at time step *t*.

Table 2: The possible arrangements of Thai NPs and VPs.

Noun Phrases	**Noun Phrases (cont.)**	**Verb Phrases**
H-Ma	H	Nuc
H-Mi-Ma	H-Mi	Nuc-Aux2
H-Q-Ma	H-Q	Nuc-M
H-Ma-Q	H-D	Nuc-Aux2-M
H-D-Ma	H-Mi-Q	Nuc-M-Aux2
H-Mi-Q-Ma	H-Q-Mi	Aux1-Nuc
H-Q-Mi-Ma	H-Mi-D	Aux1-Nuc-Aux2
H-Mi-D-Ma	H-Q-D	Aux1-Nuc-M
H-Q-D-Ma	H-D-Q	Aux1-Nuc-Aux2-M
H-D-Q-Ma	H-Mi-Q-D	Aux1-Nuc-M-Aux2
H-Mi-Q-D-Ma	H-Mi-D-Q	
H-Mi-D-Q-Ma	H-Q-Mi-D	
H-Q-Mi-D-Ma		
H-Q-Mi-D-Ma		

The probability of a sequence of *T* hidden states PC^T = *{PC(1), PC(2), …, PC(T) }* can be written as:

$$p(PC^T) = \prod_{t=1}^{T} p(PC(t) \mid PC(t-1)) \quad (3)$$

The probability that the model produces the corresponding sequence of POS tag tag^T, given a sequence of PCs PC^T can be written as:

$$p(tag^T \mid PC^T) = \prod_{t=1}^{T} p(tag(t) \mid PC(t)) \quad (4)$$

Then, the probability that the model produces a sequence tag^T of visible POS tag states is:

$$p(tag^T) = \arg\max_{PC_{1,n}} \prod_{t}^{T} p(tag(t) \mid PC(t))\, p(PC(t) \mid PC(t-1)) \quad (5)$$

The Baum-Welch [11] learning algorithm is applied to determine model parameters, i.e., a_{ij} and b_{jk}, from an ensemble of training samples.

Given a sequence of visible state tag^T, the Viterbi algorithm [11] is used to find the most probable sequence of hidden states by recursively calculating $p(tag^T)$ of visible POS states. Each term $p(tag(t)|PC(t))$ $p(PC(t)|PC(t-1))$ involve only $tag(t)$, $PC(t)$, and $PC(t-1)$ by the following definition:

$$\delta_t(j) = \begin{cases} 0, & t = 0 \text{ and } j \neq \text{initial state} \\ 1, & t = 0 \text{ and } j = \text{initial state} \\ \arg\max_i \delta_{t-1}(i) a_{ij} b_{jkt}, & \text{otherwise} \end{cases} \quad (6)$$

Figure 3 shows a phrase identification model of string “เพื่อนจะขอยืมหนังสือเล่มนี้ เพราะΦ_1ซื้อไม่ได้Φ_2 ดังนั้นΦ3จึงต้องยืมหนังสือฉัน” (A friend’s going to borrow this book. Because she (Φ_1) hasn’t been able to buy it (Φ_2). Therefore she (Φ_3) must borrow it from me.) POS tags of the string is “เพื่อน (A friend-NCMN) จะขอ (is going to-XVMM) ยืม (borrow-VACT) หนังสือ (book-NCMN) เล่ม (numerative-CNIT) นี้ (this-DDAC) เพราะ (Because-CONJ) เธอ (she(Φ_1)-PPRS) ไม่ (hasn’t been-NEG) สามารถ (able to-XVMM) ซื้อ (buy-VACT) มัน (it(Φ_2)) ดังนั้น (Therefore-CONJ) เธอ (she(Φ_3)-PPRS) จึงต้อง (must-XVMM) ยืม (borrow-VACT) หนังสือ(book-NCMM) ฉัน (me-PPRS)”.

The hidden state of a phrase model consists of H(NCMN-book (2/4), -friend (1/4); PPRS-me (1/4)), D(CNIT-numerative (1/2); DDAC-this (1/2)), Discourse-marker(CONJ-because (1/2), -therefore (1/2)), Aux1(XVMM-is going to (1/4), -must (1/4), -able to (1/4); NEG-hasn’t been (1/4)) and Nuc(VACT-borrow (2/3), -buy (1/3)).

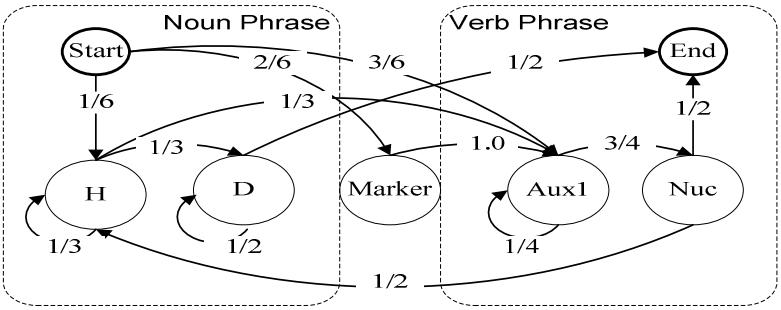


Fig. 3. A phrase identification model.

		เพื่อน	จะขอ	ยืม	หนังสือ	เล่ม	นี้	
	Start	NCMN	XVMM	VACT	NCMN	CNIT	DDAC	END
Start	1	0	0	0	0	0	0	0
H	0	1/6*3/4	0	0	$8*10^{-3}$	0	0	0
D	0	0	0	0	0	$1*10^{-3}$	$3*10^{-4}$	0
Marker	0	2/6*0	0	0	0	0	0	0
Aux1	0	3/6*0	$3*10^{-2}$	0	0	0	0	0
Nuc	0	0	0	$2*10^{-2}$	0	0	0	0
End	0	0	0	0	0	0	0	$1*10^{-4}$
T =	0	1	2	3	4	5	6	7
Output	Start	H	Aux1	Nuc	H	D	D	End

Fig.4. The results of Viterbi tagging on the phrase identification model in Fig 3.

4.2 EDU Boundary Determination

After we determine NPs and VPs, another HMM on EDU constituents (shown in Fig. 5.) is then created to determine the boundaries of EDUs. This model can handle the subject and object omission problems, discussed earlier.

Fig. 5 shows an example of the EDU segmentation model for an EDU "เพื่อน-จะขอ-ยืม-หนังสือ-เล่ม-นี้" (A friend's going to borrow this book.)

The EDU segmentation model can be expressed as:

$$p(tag^T) = \arg \max_{EDUC_{1,n}} \prod_t^T p(tag(t) \mid EDUC(t)) p(EDUC(t) \mid EDUC(t-1)) \quad (7)$$

where *EDUC(t)* is EDU constituent at time step *t*, and *tag(t)* is the phrase tag at time step *t*.

The expression, *p(EDUC(t)|EDUC(t-1))* is the probability of EDU constituent (*EDUC*) at time *t* given the previous *EDUC(t-1)*, and *p(tag(t)|EDUC(t))* is the probability of phrase tag *tag(t)* given *EDUC(t)*.

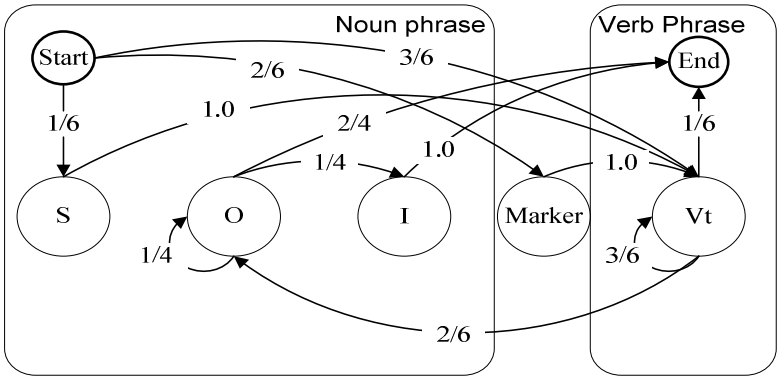


Fig.5. An example of a Thai EDU segmentation model.

		เพื่อน	จะขอ	ยืม	หนังสือ	เล่ม	นี้	
	Start	H	Aux1	Nuc	H	D	D	END
Start	1	0	0	0	0	0	0	0
S	0	1[1/6*1]	0	0	0	0	0	0
O	0	0	0	0	$3*10^{-3}$	$6*10^{-4}$	$1*10^{-4}$	$5*10^{-5}$
I	0	0	0	0	0	0	0	0
Marker	0	1[2/6*0]	0	0	0	0	0	0
Vt	0	1[3/6*0]	$9*10^{-2}$	$2*10^{-2}$	0	0	0	0
End	0	0	0	0	0	0	0	0
t =	0	1	2	3	4	5	6	7
Output	Start	S	Vt	Vt	O	O	O	End

Fig.6. The results of Viterbi tagging
on the Thai EDU segmentation model in Fig.5.

4.3 EDU Constituent Grouping

Once EDU boundaries are determined, syntactic rules in Table 1 are then applied to group EDU constituents into a larger unit that will be used to match the semantic rules in further steps, For example a string "เพื่อน-จะขอ-ยืม-หนังสือ-เล่ม-นี้" (A friend's going to borrow this book.), the result from the Viterbi tagging on the EDU segmentation model is S, Vt, Vt, O, O, O. The matched rule of "NP_O-NP_S-Vt-NP_O" is applied, and the result becomes: "NP_S – (V, V)$_t$ – (NP, NP, NP)$_O$."

5 THE REFERENCES SECTION

In this section, we describe our proposed technique based on semantic rules derived from Thai linguistic characteristics to construct an RS tree from a corpus. The rules are classified into three types which are Absence, Repetition, and Addition rules [2, 3, 4, 12, 17]. Given a pair of EDUs, an author may write by using any combination of the rules. A similarity measure is calculated from these rules, and a hierarchical clustering algorithm employing this measure is used to construct an RS tree.

5.1 Semantic Rules for EDU Relations

Absence Rules

In Thai language, it has been observed that frequently in writings some constituents of an EDU may be absent while its meaning remains the same. In the example below, the NP (object) "ขนม" (dessert) is absent from the anaphoric EDU, according to rule Φ (O, O).

Cataphoric EDU (Vt-O) : อยากจะทำขนมไหม (Would you like to make a dessert?)
Anaphoric EDU (Vt) : อยากจะทำ (Yes, I do.)

Repetition Rules

It has been observed that frequently an anaphoric EDU relates to its cataphoric EDU by a repetition of NP (subject, object) or a preposition phrase (PP) functioning as a modifier of a nucleus or a verb phrase (VP). In the following example, two EDUs relate by a repetition of an object (NP) "บ้าน" (house), according to the rule ฯ (O, O).

Cataphoric EDU (Vtt-O-I) : ผมกำลังจะขายบ้านให้เขา (I'm going to sell him a house.)
Anaphoric EDU (Vt-O) : จะขายบ้านหลังไหน (Which house are you going to sell?)

Addition Rules

It has been observed that frequently an anaphoric EDU relates to its cataphoric EDU by an addition of a discourse marker, and possibly accompanied by Absence and/or Repetition rules. In the example below a discourse marker "เพราะ" (because) is added in front of the anaphoric EDU, according to the rule Д (Marker, Before).

Cataphoric EDU (Vtt-O-I) : ฉันอยากจะยืมหนัง (I want to borrow films.)

Anaphoric EDU (Vt-O) : เพราะหาซื้อไม่ได้ (because I have not been able to buy it.)

Table 3 lists Repetition, Absence, and Addition rules, for example, я (S, S) means that the subject of the cataphoric EDU is repeated in the anaphoric EDU; Φ(S, S) means that the subject is present in the cataphoric EDU but absent from the anaphoric EDU; and Д (Marker, Before) means that a discourse marker is added in front of this particular EDU.

5.2 EDU Similarity

Similarity between two EDUs can be calculated from the semantic rules in Table 3, as follows:

5.2.1 Feature Calculations

Given a pair of EDUs, for each rule, an EDU calculates a feature vector which consists of the following elements: Subject, Absence of Subject, Object, Absence of Object, Preposition, Absence of Preposition, Nucleus, Modifier Nucleus, Head, Absence of Head, Modifier Head, Absence of Modifier Head, Marker Before, and Marker After elements. The value of an element is dependent upon the type of rule, as follows:

Table 3: Repetition, Absence, and Addition rules.

Repetition (Я)	Absence (Ф)	Addition (Д)
я (S, S)	Ф (S, S)	Д (Marker, After)
я (O, S)	Ф (O, S)	Д (Marker, Before)
я (S, O)	Ф (S, O)	Д (Key Phrase, After)
я (O, O)	Ф (O, O)	Д (Key Phrase, Before)
я (S, Prep)	Ф (Only H, H)	
я (O, Prep)	Ф ((H, M), H)	
я (Prep, S)	Ф ((H, M), M)	
я (Prep, O)	Ф (S, Prep)	
я ((S, Prep), (S, Prep))	Ф (O, Prep)	
я ((O, Prep), (S, Prep))	Ф (Prep, S)	
я ((Prep, Prep), (S, Prep))	Ф (Prep, O)	
я ((S, Prep), (O, Prep))		
я ((O, Prep), (O, Prep))		
я((Prep, Prep), (O, Prep))		
я (Only H, Only H)		
я (H, M)		
я (Only M, Only Nuc)		
я (Only M, Only M)		
я ((Nuc, M), (Nuc, M))		

The following example is used to illustrate calculations related to semantic rules:

EDU1: ชาวบ้าน (Subject) ประกอบ (Nucleus) อุตสาหกรรมในครอบครัว (Object) (The villagers
perform the family-industry.)

EDU2: และ (Before) Ф (Absence of Subject) หวงแหน (Nucleus) สมบัติของชาติ (Object) (and
protect properties of the nation.)

EDU3: อุตสาหกรรมในครอบครัว (Subject) จึงเป็น (Nucleus) สมบัติของชาติ (Object) (Therefore, the
family-industry is a property of the nation.)

To describe the calculations related to semantic rules, the following notations will be used. C_{Cat} is a constituent of the cataphoric EDU, C_{Ana} is a constituent of the anaphoric EDU, Pos_{Cat} is the position of cataphoric EDU, and Pos_{Ana} is the position of anaphoric EDU. *X:Y* where *X* can be either Cataphoric or Anaphoric, and *Y* is an element in the vector of X, e.g., *Cataphoric:Subject* is the Subject element in the vector of the cataphoric EDU. *X:rule* is an Addition rule applied to *X* (i.e., a cataphoric or an anaphoric EDU).

Features based on an Absence rules:

Feature vectors of the cataphoric and anaphoric EDUs are filled for a

matched Absence rule, as follows:

$$If\ \Phi(C_{Cat}, C_{Ana})\ is\ true\ then$$
$$Cataphoric C_{Cat} = Anaphoric(Absence\ of\ C_{Ana}) = 1 - \frac{|Pos_{Cat} - Pos_{Ana}|}{Total\ \#\ of\ sentences} \quad (8)$$

In this example, the properties of EDU1 and EDU2 match with the rule *Φ(S, S)* with the absence of subject "ชาวบ้าน" (villager) in the anaphoric EDU, thus:

$$Cataphoric: Subject = Anaphoric: Absence\ of\ Subject = 1 - \frac{|1-2|}{3} \quad (9)$$

Features based on Repetition rules:

Feature vectors of the cataphoric and anaphoric EDUs is filled for a matched Repetition rule, as follows:

$$If\ \Re(C_{Cat}, C_{Ana})\ is\ true\ then$$
$$Cataphoric: C_{Cat} = Anaphoric: C_{Ana}$$
$$= \frac{|Pos_{Cat} - Pos_{Ana}|}{Total\ \#\ of\ sentences} * \frac{Total\ \#\ of\ repeating\ words}{Total\ \#\ of\ words\ in\ sentences} \quad (10)$$

In the example, the properties of EDU1 and EDU3 match with the rule я (O, S) with a repetition of an object "อุตสาหกรรมในครอบครัว" (family-industries) in the cataphoric EDU as a subject in the anaphoric EDU, thus:

$$Cataphoric: Object = Anaphoric: Subject = (1 - \frac{1-3}{3}) * (\frac{1}{3} * \frac{1}{3}) \quad (11)$$

Features based on Addition rules:

Feature vectors of the cataphoric and anaphoric EDUs is filled for a matched Addition rule, as follows:

$$\begin{array}{c} If\ Cataphoric{:}Д\ (Marker, After)\ is\ true\ then \\ Cataphoric{:}Marker\ After = Anaphoric{:}Marker\ Before = 1 \\ else\ if\ Anaphoric{:}Д\ (Marker, Before)\ is\ true\ then \\ Anaphoric{:}Marker\ Before = Cataphoric{:}Marker\ After = 1 \end{array} \quad (12)$$

In this example, the properties of EDU1 and EDU2 match with the rule Д (Marker, Before) at EDU2, thus:

$$Anaphoric{:}Marker\ Before = Cataphoric{:}Marker\ After = 1 \quad (13)$$

5.2.2 Rule Scoring

After for each rule, the two vectors of the EDU pair are calculated, the vectors are then combined into a rule score which depends on the type of rule and the distance between the two EDUs, as follows:

Absence and Repetition Rules:
These rules consist of two parts (cataphoric and anaphoric). If both parts of an Absence or a Repetition rule are true, then the rule is true. But if a part of an Absence or a Repetition rule is false, then the rule is false, thus:

$$if \mid Pos_{Cat} - Pos_{Ana} \mid < MD \ \ then$$

$$RS_{\substack{Absense \\ or \\ Repetition}} = [Magnitude\ of\ \ EDU_{Cataphoric} \ * \ Magnitude\ of\ \ EDU_{Anaphoric}] \quad (14)$$

where Pos_{Cat} and Pos_{Ana} are the positions of cataphoric and anaphoric EDUs, and MD is the maximum distance between the EDUs (from experiments $MD = 4$ in this research)

Addition Rules:
In this type of rules, if one part of the rule is true, then the rule is true, thus:

$$if \mid Pos_{Cat} - Pos_{Ana} \mid < MD \ then$$

$$RS_{Addition} = [Magnitude\ of\ \ EDU_{Cataphoric} + Magnitude\ of\ \ EDU_{Anaphoric}] \quad (15)$$

5.2.3 Rule Scoring
Once rule scores are available, similarity between two EDUs (cataphoric and anaphoric) can be calculated as a sum of all the rule scores (each normalized into a range from 0 to 1) according to the CombSum method [8].

6 RHETORICAL TREE CONSTRUCTION

A hierarchical clustering algorithm is applied to create an RS tree where each sample (an EDU in this case) begins in a cluster of its own; and while there is more than one cluster left, two closest clusters are combined into a new cluster, and the distance between the newly formed cluster and each other cluster is calculated. Hierarchical clustering algorithms studied in this research are shown in Table 4, and two example RS trees created from two different algorithms are shown in Fig. 7.

Table 4. Hierarchical clustering algorithms studied in this research.

Algorithms	Distance Between Two Clusters
Single Linkage	The smallest distance between a sample in cluster A and a sample in cluster B.
Unweighted Arithmetic Average	The average distance between a sample in cluster A and a sample in cluster B.
Neighbor Joining	A sample in cluster A and a sample in cluster B are the nearest. Therefore, define them as neighbors.
Weighted Arithmetic Average	The weighted average distance between a sample in cluster A and a sample in cluster B.
Minimum Variance	The increase in the mean squared deviation that would occur if clusters A and B were fused.

7 EXPERIMENTAL EVALUATION

7.1 Rule Scoring

In order to evaluate the effectiveness of the EDU segmentation process, a consensus of five linguists, manually segmenting EDUs of Thai family law, is used. The dataset consists of 10,568 EDUs in total.

The EDU segmentation model is trained with 8,000 random EDUs, and the rest are used to measure performance.

The training continues until the estimated transition probability changes no more than a predetermined value of 0.02, or the accuracy achieves 98%.

The performances of both phrase identification and EDU segmentation are evaluated using recall (Eq. 16) and precision (Eq. 17) measures, which are widely used to measure performance.

$$\mathrm{Re}\,call = \frac{\#\,correct\ \ (phrases\ \ or\ \ EDUs)\ \ identified\ \ by\ \ HMM}{\#\,(phrase\ \ or\ \ EDUs)\ \ identified\ \ by\ \ linguists} \tag{16}$$

$$\mathrm{Pr}\,ecision = \frac{\#\,correct\ \ (phrases\ \ or\ \ EDUs)\ identified\ \ by\ \ HMM}{total\ \#\,(phrases\ \ or\ \ EDUs)\ identified\ \ by\ \ HMM} \tag{17}$$

The results show that the proposed method achieves the recall values of 84.8% and 85.3%; and the precision values of 93.5% and 94.2% for phrase identification and EDU segmentation, respectively.

7.2 Evaluation of EDU Constituent Grouping

In order to evaluate the effectiveness of the EDU constituent grouping, three corpuses are used which consist of Absence data (84 EDUs), Repetition data (117 EDUs) and a subset of the Family law with 367 EDUs). The Absence data contains EDUs mostly those following the Absence rules while the Repetition data contains mostly those following the Repetition rules. Five linguists create training and testing data sets by manually grouping EDU constituents.

Table 5 shows the results of grouping EDU constituents (subject (S), object (O), indirect object (I) and nomen (N)) by using rules based on NPs, assuming the positions of verb phrases (Vi, Vt and Vtt) are known. From the results, in general all rules, except NP_O-NP_S-Vtt-NP_I and NP_I-NP_S-Vtt-NP_O, perform well.

Table 5: Performance of grouping EDU constituents

Rules	Absence Data	Repetition Data	Family Law
NP_S-Vi-NP_S	NP_S (100%)	NP_S (100%)	NP_S (100%)
NP_O-NP_S-Vt-NP_O	NP_S & NP_O (100%)	NP_S &NP_O (100%)	NP_S &NP_O (100%)
NPS-Vtt-NPO-NPI	NP_S &NP_O&NP_I (100%)	NP_S &NP_O&NP_I (100%)	NP_S &NP_O&NP_I (100%)
NP_O-NP_S-Vtt-NP_I NP_I-NP_S-Vtt-NP_O	NP_S (100%), NP_O&NP_I (91.37%)	NP_S (100%), NPO&NP_I (79.59%)	NP_S (100%), NP_O&NP_I (90.21%)
N-N	NP_N (100%)	NP_N (100%)	NP_N (100%)

To further resolve ambiguities with respect to these two rules, a probability table of terms in positions of NP_I and NP_O following Vtt ($P(Vtt| NP_I, NP_O)$) is used. The results of determining functions of EDU constituents by using the rules based on NPs together with the probability table show higher performance for Absence data (92.24%), Repetition data (85.78%), and Family law (93.71%).

7.3 Evaluation of Thai RS Tree Construction

In order to evaluate the effectiveness of the proposed Thai RS tree construction process, linguists manually construct the rhetorical structure trees of three texts used above with a total of 568 EDUs. The

algorithms are evaluated by using recall (Eq. 18) and precision (Eq. 19) measures. Recall and precision are calculated with respect to how close an RS tree constructed from the proposed technique to that created by a consensus of the linguists.

$$\text{Re } call = \frac{\#\, correct \;\; internal \;\; nodes \;\; identified \;\; by \;\; RS \;\; Tree}{\#\, internal \;\; nodes \;\; identifi \;\; ed \;\; by \;\; linguists} \quad (18)$$

$$\text{Pr } ecision = \frac{\#\, correct \;\; \text{internal nodes} \;\; identified \;\; by \;\; \text{RS Tree}}{\text{Total \# of internal nodes} \;\; identified \;\; by \;\; \text{RS Tree}} \quad (19)$$

For the Absence and Repetition data sets, though relations between EDUs follow mostly Absence rules and Repetition rules, respectively, in reality when examined in details, many types of rules are used together in writing. For example,

Anaphoric EDU (S-Vt-O) : บุรุษไปรษณีย์ (S) จะคัดเลือก (Vt) จดหมาย (ย O)
(A Postman will sort letters)

Cataphoric EDU ((S)-Vt-O) : และ (Д) (Φ S) รับส่ง (Vt) จดหมาย (ย O)
(And will deliver letters)

Table 6 shows calculations of recall and precision of RS trees created by the Minimum Variance and Unweighted Arithmetic Average algorithms, in Fig. 7.

Table 7 shows the results of evaluating Thai RS Tree construction on the three data sets. The performance on the Family law dataset which combines many kinds of rules in its content is 94.90% recall and 95.21% precision. The results also show that Unweighted Arithmetic Average clustering algorithm gives the best performance for Thai RS Tree construction.

8 CONCLUSIONS

Thai rhetorical structure tree (RST) construction is an important task for many textual analysis applications such as automatic text summarization and question-answering. This article proposes a novel two-step technique to construct Thai RS tree combining machine learning techniques with linguistic properties of the language.

Table 6: RS tree construction performance of two clustering algorithms

The correct RS tree	Minimum Variance	Unweighted Arithmetic Average
3’	3’	3’
4’	4’	4’
1’	1’	1’
9’	9’	6’
2’	2’	2’
5’	5’	5’
6’	6’	
7’	7’	
8’	8’	
		7’
		8’
		9’
		10’
	Precision = 9/9	Precision = 6/10
	Recall = 9/9	Recall = 6/9

Table 7: Performance of the RS tree construction

Data	Num EDUs	Clustering Method	Recall	Precision
Absence	84	Neighbor Joining	87.23	89.13
		Single Linkage	82.97	84.78
		Un weighted Arithmetic Average	87.23	89.13
		Minimum Variance	89.40	91.30
		Weighted Arithmetic Average	87.23	89.13
Repetition	117	Neighbor Joining	89.70	91.04
		Single Linkage	83.82	85.07
		Unweighted Arithmetic Average	89.70	91.04
		Minimum Variance	77.94	79.10
		Weighted Arithmetic Average	89.70	91.04
Family-Law	367	Neighbor Joining	85.98	86.26
		Single Linkage	64.01	64.21
		Unweighted Arithmetic Average	94.90	95.21
		Minimum Variance	63.37	63.57
		Weighted Arithmetic Average	90.44	90.73

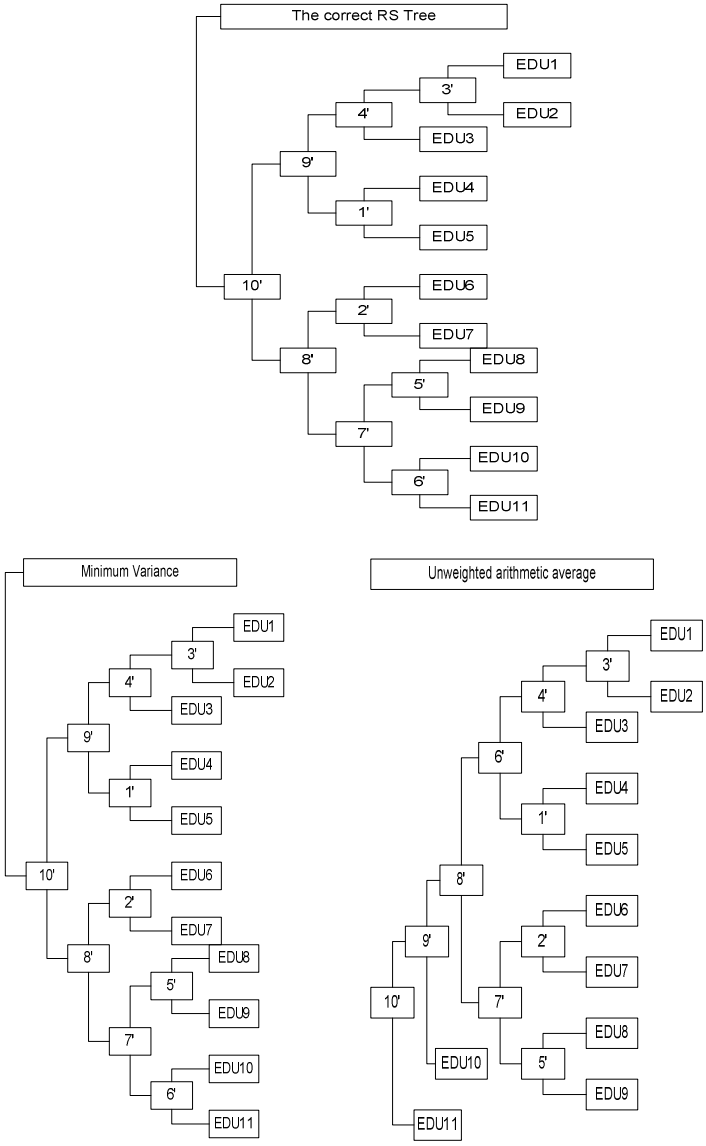


Fig. 7. RS trees from two hierarchical clustering algorithms

First, phrases are determined and then are used to segment elementary discourse units (EDUs). The phrase segmentation model is a hidden Markov model constructed from the possible arrangements of Thai phrases based on part-of-speech of words, and the EDU segmentation model is another hidden Markov model constructed from the possible phrase-level arrangements of Thai EDUs. Linguistic rules are applied after EDU segmentation to group related constituents into a large unit. Experiments show the EDU segmentation effectiveness of 85.3% and 94.2% in recall and precision, respectively.

A hierarchical clustering algorithm whose similarity measure derived from semantic rules of Thai language is then used to construct an RS tree. The technique is experimentally evaluated, and the effectiveness achieved is 94.90% and 95.21% in recall and precision, respectively.

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