Comparative Study of Using Word Co-occurrence to Determine Symptoms from Texts

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ABSTRACT

The research approach is to determine the symptom explanation from downloaded hospital documents to construct the semantic relations between disease-topic names and symptom explanation for enhancing the automatic problem-solving system. However, this paper aims to comparative study of using different word co-occurrence sizes as the two word co-occurrence and the N word co-occurrence on verb phrases to identify the symptom-concept sentences. We also use these word co-occurrences to determine the boundary of the consecutive symptom-concept sentences through the machine learning technique and the similarity-score determination. The research results provide the high precision of the symptom determination from the documents.

1. Introduction

The research objective is the comparative study of using word co-occurrence to determine the explanation of disease-symptom-concept sentences from the downloaded health-care documents on the hospital web-boards. The research results are beneficial to the automatic diagnosis system. Moreover, the disease symptom explanation mostly consists of event expressions on several EDUs (where EDU is an Elementary Discourse Unit expression defined as a simple sentence or a clause, [1]) as the symptom-concept explanation on a document of a certain disease as follow.

Example1.

Topicname: โรคกระเพาะ/StomachDisease

EDU1symptom: "[หนู]ปวดท้องอยู่ข้างหนัก" / "[หนู/A user] ปวด/pain หนัก

/abdominal อยู่ข้างหนัก/heavily" ([A user] has a stomachache heavily.)

EDU2symptom: "[หนู] มีแก๊สในกระเพาะ" / "[หนู/He] มี/has แก๊ส/gas มาก/a lots ในกระเพาะ/inside stomach"

([He] has lots of gas in the stomach.)

EDU3symptom: "อาการมักเป็นหลังอาหารเย็น" / "อาการ/Symptom มักเป็น/mostly occurs หลังอาหารเย็น/after dinner" (The symptom mostly occurs after dinner.)

EDU4: "[หนู] สงสัยเป็นโรคกระเพาะ" ([He] doubts to get gastropathy.)

where the [...] symbol means ellipsis. A symptom-concept EDU boundary occurs on EDU1, EDU2, and EDU3. According to Example1, the research emphasizes on the event expressions by verb phrases because of most symptom-concept expressions on the verb phrases of EDUs. Each verb phrase is based on the following linguistic pattern after stemming words and eliminating stop words.

EDU 2 NP1 VP

VP 2 V1 | V1 NP2 | V1 Adverb | V2 NP3 | V2 NP3 VP | V2 Adj V1

2 Vstrong | Preverb Vstrong

V2 2 Vweak | Preverb Vweak

NP1 2 Noun1 | Noun2 | Noun3

NP2 2 Noun2 | Noun2 NP2 | Noun2 AdjectivePhrase NP3 2 Noun3 |

Noun3 Adj prep NP2

Noun1 2 {ผู้ป่วย/patient' 'โรค/disease' ...} ;

Noun2 2 {อวัยวะ/organ' 'บริเวณ/area' 'อุจจาระ/stool'

...} Noun3 2 {อาการ/symptom' 'แผล/scar' 'รอย/mark'

'ไข้/fever' 'ผื่น/rash' 'หนอง/pus' ...}

Vstrong 2 {คลื่นไส้/nauseate' 'อาเจียน/vomit'

'ปวด/pain' 'เจ็บ/pain' 'แน่น/constrict' 'คัน/itchy' ...}

Vweak 2 {เป็น/be' 'มี/have' 'รู้สึก/feel'}

Adv 2 {ยาก/difficultly' ...} ; Adj 2 {สี.../...color' 'เหลว/watery' ...} ; Preverb

2 {ไม่/not' ...}

where NP1, NP2, and NP3 are noun phrases. VP is a verb phrase. Vstrong is a strong verb set with the symptom concept. Vweak is a weak verb set which need more information to have the symptom concept. Noun3 is a noun set with a symptom concept. Adv is an adverb set with the symptom concept. Adj is the adjective set with the symptom concept. prep is a preposition.

Moreover, previous researches have worked on event extraction from text [2, 3, 4]. In 2011, [2] applied syntactic and lexical constraints on binary relations expressed by verb phrases (called relation phrases) for the Open Information Extraction system, REVERB. They implemented a verb-noun combination on the relation phrase to match the POS tag pattern. The research results with more than 30% of REVERB's extractions are at precision 0.8. Whereas [3] proposed methods for filtering harmful sentences based on multiple word co-occurrences. They compare harmless rate between two-word co-occurrence and three-word co-occurrence. The precision of identify and filtering the harmful sentences through three-word co-occurrence method exceeds 90% whereas the precision of the two-word co-occurrence is under 50%. In 2014, [4] worked on a model for identifying causality in verb-noun pairs to encode cause or non-cause relation. The result of this research achieves 14.74% and 41.9% F-scores for the basic supervised classifier. Thus, most of previous researches identify an event by two-word co-occurrence as verb-noun co-occurrence. Whereas the symptom-concept expression on each EDU of our research mostly consists of several words (see Example 1). However, our research contains two problems of determining the explanation of the symptom-concept EDUs; how to identify an EDU verb phrase having symptom concept (see Example1) and how to determine the symptom explanation as the symptom-concept

EDU boundary, i.e. EDU1-EDU3 of the Example1. Therefore, we propose using the different word co-occurrence sizes; the co-occurrence between two words (called Word-Co) and the co-occurrence between N words (called N-Word-Co), on the EDU verb phrase for comparative study of using Word-Co and N-Word-Co to determine the symptom-concept EDU. With regard to the symptom-concept EDU boundary determination, we apply Support Vector Machine (SVM) [5] to solve the boundary having Word-Co as input features and we apply the similarity score [6] to solve the boundary having N-Word-Co as input features. Moreover, we also determine the N-Word-Co size (or the N value) by SVM.

The research consists of 3 sections. In section 2, the research framework of determining the symptom EDU vector is described and we evaluate and conclude our proposed model in section3.

2. A Framework of Determining Symptom Vector

Figure1. System Overview

There are three main steps in determining the symptom vector or the symptom-concept EDU vector by using the Word-Co or N-Word-Co technique, Corpus Preparation step, Learning Step and Symptom Vector Determination Step.

2.1 Corpus Preparation

This step is the preparation of corpus in the form of EDU from the medical-care documents on the hospital's web-board (<http://haamor.com/>). The step involves with using Thai word segmentation tools [7] including Name entity [8] followed by EDU segmentation [9]. These annotated EDUs are used as an EDU corpus which contains 3000 EDUs of gastrointestinal tract diseases and childhood diseases and is separated into 2 parts; the first part of 2000EDUs for the learning step of both Word-Co and N-Word-Co; and the second part of 1000 EDUs for determining the symptom-concept EDU boundary. We then semi-automatically annotate the Word-Co expressions with symptom concepts for the w1 and w2 tags as Word-Co and for the w1 through wj as N-Word-Co after stemming words and the stop word removal as shown in Fig.2. All symptom concepts are referred to WordNet (<http://word-net.princeton.edu/obtain>) and MeSH (<https://www.nlm.nih.gov/mesh/>) after translating from Thai to English, by Lexitron (<http://lexitron.nectec.or.th/>).

Figure2. Word Co-Occurrence Annotation

2.2 Learning

2.2.1 Word-Co Learning. We collect each Word-Co feature, w1w2 or vco wco, with the symptom concept into VW from annotated corpus where VW is a Word-Co set with the symptom concepts; w1 is a verb represented by vco; and w2 is a co-occurred word represented by wco. VW is used for identifying and extracting the consecutive symptom-concept Word-Co occurrences for learning the EDU's Word-Co boundary

with the symptom concept by SVM (using Weka, <http://www.cs.wakato.ac.nz/ml/weka/>). SVM is the linear kernel: the linear function, $f(x)$, of the input $x = (x_1..x_n)$

assigned to the positive class if $f(x) \geq 0$, and otherwise to the negative class if $f(x) < 0$, can be written as

$$f(x) = \langle w \cdot x \rangle + b \quad (1)$$

$$= \sum_{j=1}^n w_j x_j + b$$

where x is a dichotomous vector number, w is a weight vector, b is a bias, and $(w,b) \in \mathbb{R}^n$ are the parameters that control the function. The SVM learning is to determine w and b for each Word-Co feature, $v_{co-j} w_{co-j}$ in each Word-Co pair, $v_{co-j} w_{co-j} v_{co-j+1} w_{co-j+1}$, from the supervised learning of SVM by sliding the window size of two consecutive EDUs with one sliding EDU distance where $j = 1, 2, \dots, n$ and n is End-of-Boundary.

2.2.2. N-Word-Co Learning. In regard to Eq. 2, the features used for learning N-Word-Co size by SVM are obtained by the following concept sets: Verbstrong, Verbweak, Noun1, Noun2, Noun3, Adj, and Adv. The SVM learning is to determine w and b for each word feature, w_j (or x_j) in each word-concept pair $(w_j w_{j+1})$ with a symptom concept. The N-Word-Co size/boundary learning from $w_j w_{j+1}$ of VP is the supervised learning of SVM by sliding the window size of two consecutive words with one sliding word distance after stemming words and the stop word removal. Where $j=1,2,\dots,n$ and n is End-of-Boundary and is equivalent to the N value of N-Word-Co size.

2.3 Symptom-Concept EDU Boundary Determination

2.3.1 Symptom-Concept EDU Boundary Determination by Using Word-Co. After using VW to identify a symptom concept EDU from the testing corpus, the w vector of all $v_{co-j} w_{co-j}$ from the SVM learning are used to determine the boundary of the symptom-concept EDUs with Eq. 1 by sliding the window size of two consecutive EDUs with one sliding EDU distance. If $f(x) < 0$ then the boundary is ended as a symptom vector; otherwise continuing.

Symptom-Concept EDU Boundary Determination by Using N-Word-Co. The symptom-concept EDU boundary is determined after the N-Word-Co size determination and extraction. After $w_1 \in V_{strong} \cup V_{weak}$ and w_1 is the first word of VP on the testing corpus, the w vector of all w_j from the SVM learning in section 2.2.2 which are used to determine and extract the N-WordCo size/boundary with symptom-concept into the matrix vector W of symptom concepts with Eq. 1 by sliding the window size of two consecutive words with one sliding word distance. If $f(x) < 0$ then the boundary is ended as a word vector of N-Word-Co; otherwise continuing. The symptom-concept EDU boundary is then determined by the similarity score determination as Max Similarity Score (MaxSimScore) [6] in Eq. 2. MaxSimScore is determined between the N-Word-Co of the testing corpus's EDU and the candidate N-Word-Co expressions from W . The N-Word-Co concept of each consecutive EDU verb phrase is the symptom concept if $\text{MaxSimScore} \geq 0.9$ to W ; otherwise the symptom vector is ended.

$$\text{MaxSimScore} = \text{ArgMax} \left(\text{similarity}_{i=1}^{\text{Cardinality}} \left(\frac{|NWC_{corpus} \cap NWC_{candidate}_i|}{|NWC_{corpus}| \times |NWC_{candidate}_i|} \right) \right) \quad (2)$$

where Cardinality is the number of N - Word - Co elements of W

W is the Matrix vector of N - Word - Co (the N - Word - Co set) with the symptom concept

$NWC_{candidate}$ is a candidate N - Word - Co element of The N - Word - Co set with the symptom concept

NWC_{corpus} is an N - Word - Co of EDU from the testing corpus

3. Evaluation and Conclusions

The testing corpus of 1000 EDUs of gastrointestinal tract diseases and childhood diseases is used for evaluating the symptom-concept-EDU-boundary determination. Both evaluations of the symptom vector determinations by using Word-Co and by using N-Word-Co from the testing corpus are based on the precision and the recall which are evaluated by three expert judgments with max win voting. The precisions of determining the symptom-concept EDU boundaries are 91.3% and 84.8% with the recalls of 69.2% and 73.1% by using N-Word-Co and Word-Co respectively. The reason of low recall is the anaphora problem, i.e. '(บางสิ่ง/ something)/pronoun' occurrence on VP as follow.

VP="(รู้สึก/feel)/serialverb (มี/ have)/weak-verb
(บางสิ่ง/ something)/pronoun
(ข้างใน/inside)/prep (จมูก/nose)/noun (ระหว่าง/ during)/prep (เวลาเช้า/ morning)/noun"
("feel to have something inside the nose during the morning")

However, the research results provide the higher precision by using N-Word-Co and the higher recall by using Word-Co to determine the symptom explanation from the documents. Thus, the symptom explanation is determined to construct the semantic relation as the diseaseName- symptomExplanation relation where the disease-names are obtained by the document topics. The relation is beneficial to the automatic diagnosis of the problem solution. Moreover, the proposed method of using word co-occurrence to determine the symptom explanation can also be applied to the other areas such as the industrial finance problem explanation.

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