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Lexical Resource for Medical Events: A Polarity Based Approach

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Abstract—**The continuous sophistication in clinical information processing motivates the development of a dictionary like WordNet for Medical Events in order to convey the valuable information (e.g., event definition, sense based contextual description, polarity etc.) to the experts (e.g. medical practitioners) and non-experts (e.g. patients) in their respective fields. The present paper reports the enrichment of medical terms such as identifying and describing events, times and the relations between them in clinical text by employing three different lexical resources namely seed list of medical events collected from SemEval 2015 Task-6, the WordNet and an English medical dictionary. In particular, we develop WordNet for Medical Events (WME) that uses contextual information for word sense disambiguation of medical terms and reduce the communication gap between doctors and patients. We have proposed two approaches (Sequential and Combined) for identifying the proper sense of a medical event based on each of the three types of texts. The polarity lexicons e.g., SentiWordNet, Affect Word List and Taboda's adjective list have been used for implementing the polarity based Word Sense Disambiguation of the medical events from their glosses as extracted from the lexical resources. The proposed WME out-performed a previously proposed Lesk Word Sense Disambiguation in the range of 10-20%.**

Keywords— Medical Event; WordNet; polarity; Word Sense Disambiguation

I. INTRODUCTION

In the clinical domain, the representation of a lexical resource can be considered as a challenging task due to the involvement of several challenges viz. sense disambiguation, polarity classification and scarcity of clinical texts. However, the challenge was also introduced in this domain due to the lack of involvement of the domain experts [4]. To cope up with the challenges since few years, several lexical resources were designed based on WordNet [1] [2] [5] [9]. WordNet, is a tool that can determine the syntactic category of a word such as relation to other nouns in an organized hierarchy. It is observed that the researchers attempted to develop a number of such resources like Medical WordNet to bridge the gap between experts and non-experts [1] [2] [14] [25]. However, medical text is unstructured since doctors do not like to fill form and prefer free-form notes of their observations. Hence, a lexical representation is difficult due to lack any prior context or names.

Thus, in this paper we develop WordNet for Medical Events (WME), a free-standing lexical database for researchers of Natural Language Processing (NLP) in the medical domain that will allow understanding of differences in medical knowledge between doctors and patients. Our initial focus was not only to represent the medical terms for experts and non-experts but to provide a platform for reviewing and validating the medical corpus also. The experts can identify and extract the medical terms and their corresponding definitions and descriptions whereas the non-experts can avail the facility to understand generic medical information because the terms present in WME are disambiguated based on the context and polarity. Polarity detection is a popular NLP task focusing on the binary classification of snippets of text into either positive or negative [26] [27]. Common approaches to polarity detection can be categorized as either statistics based [28], e.g., algorithms based on machine learning [29], or knowledge-based [30], e.g., techniques based on common-sense knowledge [31].

In the present task, we have developed the WME by employing three lexical resources. First, a seed list of unique medical events (1654 terms) was collected from the annotated corpus of the SemEval 2015 Task-6. The file contexts of such events along with their Parts-of-Speech (POS) and polarity information were used. Similarly, the synonyms, POS and their glosses with respect to each of the medical events present in the seed list were extracted. The second resource is an English medical dictionary containing definition and POS of 11,750 medical terms. The third resource is WordNet that helps us to identify the medical events containing POS like noun (e.g. abscesses) and adjective (e.g. abnormal) in contrast to the general events (e.g. watch) that are usually tagged as verbs.

In particular, it is found in several occasions that the polarity of the medical events is not matched with the polarities appeared in their corresponding texts collected from the WordNet and English medical dictionary. Thus, a polarity based Word Sense Disambiguation (WSD) was employed on the glosses of file contexts of seed list, WordNet synonyms and English medical dictionary along with the due help from the polarity lexicons like SentiWordNet, Affect Word List and Taboda's adjective list. The proposed WME is compared with a previously proposed Lesk WSD [22] and shows a higher accuracy in the range of [10-20%].

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In next section on related works, we discuss the identification and extraction approaches of the medical events. In section 3, the medical WordNet representation technique is discussed as a system framework. The proposed polarity based WME algorithm is described in section 4. In section 5 we compare the proposed algorithms with Lesk WSD algorithm and perform an agreement study. We also evaluate the polarity lexicon on a deep sentence classification model for large scale automatic WSD. Finally, in section 6, we provide concluding statements and future scope of this task.

II. Related Work

Medical event extraction is an emerging task in Bio-medical Natural Language Processing (Bio-NLP) [8] [10] [33]. Medical events are significant keys for identifying the polarity of a clinical corpus. Hence, medical WordNet was introduced as a lexical resource for extracting the medical events and their corresponding polarity information from the corpus. For non-experts users, previous authors tried to design the taxonomy for a better understanding of the medical terms and their related information [3] [16] [18] [20] [32]. Similarly, for experts they toke help of English medical vocabularies (dictionary) for the development of medical taxonomy. Patel, Arocha and Kushniruk developed a medical information system using the medical vocabulary to arbitrate the extracted information and understand the context in suitable ways for experts and non-experts [15].

In [13] [16] [18], researchers extracted the generic information from unstructured corpus viz. web blogs, medical reports etc. in order to reduce the communication gap between experts (like doctors) and non-experts (like patients) at the time of question answering via web. Fellbaum and Smith proposed a system to justify the resources for consumer health with Medical WordNet (MEN) [12] [19]. The Medical FactNet (MFN) and Medical BeliefNet (MBN) are inherited from the Princeton medical WordNet [9]. Smith and Rosse developed the MFN for better understanding of the generic medical information for the non-experts group where as the MBN compiles a representative fraction of the beliefs about the medical phenomena [19]. Their primary motivation was to develop a medical information retrieval system for exploit the usefulness of the resources.

Resolving the ambiguity of ambiguous terms is known as word sense disambiguation (WSD). In the case of clinical corpus information, extraction is a WSD task as several medical terms have multiple unrelated senses in the lexical table [21]. To overcome this ambiguity in medical terms the polarity or sense based approach is used. In [17], the sense selection and pruning based concept was employed to enrich the ontology of the medical domain. The polarity based approach can help to reduce the gap between expert and non-expert at the time of communication and also manage the ambiguity.

The accuracy of WSD methods is known to be influenced by the choice of semantic similarity measure, source vocabularies, context window size and name entity recognition system implementation. For example, the clinical Text Analysis and Knowledge Extraction System (cTAKES) showed higher accuracy than baseline Lesk WSD when applied to medical text in [23]. In the present task, we have incorporated polarity based lexical approaches to manage the ambiguity of the medical terms (events) and identify the proper sense based description.

III. System Framwork

WordNet is found to be better than conventional dictionary when modelling the differences among consumer, media and professional medical vocabularies [3]. WordNet provides us the lexical information like POS, synonyms, the semantic relation to other words in a hierarchy and the corresponding definition of the words (medical term like event). On the other hand, the conventional dictionary helps us to identify the POS and related description of the word. Both resources have not shown much efficiency for identification of the proper sense based description for the medical terms (events). This challenge is known as Word Sense Disambiguation (WSD) [6] [7]. To resolve this challenge, we have proposed the polarity based WSD algorithm under WME. This lexical resource will help us prepare an annotation tool for the medical corpus.

A. Resource Preparation

***SemEval-2015 Task-6[1] (Seed List)*:** The present work starts with a seed list of medical events collected from the trial and training data provided by the organizers of SemEval-2015 Task-6. This task involves identifying events, times and the relations between them in clinical text. Initially, the seed list contains a total of 2479 medical terms along with various attributes such as *type* (event) along with *span context*, *polarity* (positive/negative) etc (e.g., <Tumor, *event*, "*Tumor invades through muscular wall.*", *negative*>). The span helps us to extract the relevant file context of the event from the unstructured corpus. The final version of the seed list contains 1654 number of unique medical terms. The file contexts, POS tags and polarity information of the events were kept in the seed list.

WordNet[2]: [4]. The WordNet is a resource bridge the gap between lexical and semantic relations [4]. The resource helps to identify the synonyms, POS and definition of a user given word. Therefore, in the present task, we have incorporated the WordNet for the enrichment of WME. The seed list collected from SemEval dataset was passed through the WordNet resource to determine their *POS*, *synonyms*, their respective *glosses* and *polarity* (e.g., <Abdomen, *Noun*, *(1. abdomen 2. abdominal_cavity)*, *(1. "The region of the body is vertebrate between the thorax and the pelvis." 2."The cavity containing the major viscera; in mammals it is separated from the thorax by the diaphragm."), (1. negative, 2. positive)*>).

English medical dictionary[3]: We have also incorporated English medical dictionary for better understanding of the medical terminologies. The medical dictionary was developed by H. Bateman and her group in 2007. A huge amount of

[1] http://alt.qcri.org/semeval2015/task6/
[2] http://wordnetweb.princeton.edu/perl/webwn
[3] http://alexabe.pbworks.com/f/Dictionary+of+Medical+Terms+4th+Ed.-+(Malestrom).pdf

manual editing was carried out for the pre-processing of this dictionary in order to obtain a usable resource in the field of medical text processing. The pre-processed dictionary covers the English medical words (11,750 terms) along with POS and gloss, definition and examples (e.g., <Adenoma, *Noun*, *"A benign tumor of a gland"*>).

In TABLE I, we have summarized the statistics for POS and extracted sense of the file context, WordNet definition and dictionary based description of the medical events for each of the resources, separately.

TABLE I. RESOURCE DISTRIBUTION AND STATISTICS

Different type of Data Module		Seed List	Word Net	Medical Dictionary
#A		1654	802	434
#B		15883	830	906
POS	#C	1019	504	310
	#D	488	240	76
	#E	124	49	44
Sense	#F	1338	-	-
	#G	316	-	-
#A → Medical Event Words #B → Number of Sentences #C → Noun #D → Verb #E → Adjective #F → Positive #G → Negative				

B. Corpus Statistics

We have tabularized the statistics of the above mentioned three resources with unique medical events in TABLE II. The comparative and detailed statistics of the POS distribution, number of sentences, negation words, stop words and number of synonyms have been extracted only from the glosses of the respective three resources. The detailed statistics are specified in TABLE III.

TABLE II. DIFFERENT TYPE OF UNIQUE RESOURCE EXTRACTION STATISTICS

Resource Type	Event occurrence (Unique)
Seed List	2479 (1654)
WordNet	1188 (802)
Medical Dictionary	649 (434)

The above mentioned statistics indicate that it is difficult to identify a medical event solely based on its POS hint as the POS occurrences are similar in all the three resources. It is found that the extracted glosses are not relevant with the target medical events in most cases. To resolve the ambiguity of the medical events in order to identify and enrich our WME, we have introduced two different WSD approaches based on *polarity*.

In the next Section, we discuss the polarity identification procedure from the seed list, WordNet and English Medical Dictionary and termed them as Module-1, Module-2 and Module-3, respectively throughout the paper.

TABLE III. COMPARATIVE STATISTICS

Different Basic Operation		Seed List	WordNet	Medical Dictionary
No. of Event		1654	802	434
No. of Unique Stemmed words		1276	659	402
No. of Unique Stop words		109	107	102
No. of Unique negation		23	16	18
Average length of sentences	*With Stop words*	18.57	18.09	18.8
	Without Stop words	11.19	10.9	11.5
POS Distribution	*Noun*	504	1019	310
	Verb	240	488	76
	Adjective	49	124	44
No. of Synonyms		14587	2947	2553
No. of Unique Synonyms		3783	1438	1124
No. of Events Cluster		1654	802	434

IV. POLARITY BASED WSD

The sense disambiguation is a difficult task when preparing a lexical resource such as medical event WordNet. The well known sense disambiguation algorithm like Lesk WSD uses features such as POS, unigram, bigram, term frequency (TF) etc. for identifying the common gloss of the words. Instead, we have proposed polarity based WSD approaches to resolve the problem in clinical domain. The proposed WSD approaches was designed based on the sense features extracted out of contexts. In order to develop the modules for polarity based WSD, three types of polarity lexicons were used namely SentiWordNet, Affect Word List and Taboda's adjective list.

A. Polarity Lexicon

SentiWordNet*[4]*: SentiWordNet is a popular lexical resource for sentiment analysis and opinion mining. It mainly assigns two different types of polarity scores (positive and negative) to the synsets of WordNet [11]. We have used SentiWordNet for identifying polarity of each of the glosses by combining the polarity of the words appearing in the glosses.

Affect Word List*[5]*: Affect Word List is another useful resource for emotion analysis. WordNet Affect is mainly consolidated with six different classes of emotions like *anger, disgust, fear, joy, sadness* and *surprise*. We have prepared two separate lists for positive and negative words based on their extracted scores from SentiWordNet. In comparison to the positive and negative polarity value of the affect words we have prepared the positive and negative affect word list for the task.

Taboda's Adjective List*[6]*: We have integrated another polarity lexicon, Taboda's adjective list for identifying the polarity of the glosses. Taboda's adjective list provides the positive and negative values of the words. Therefore, we assumed that such values can also be used to indicate the positive and negative polarity of the words of the glosses.

[4] http://sentiwordnet.isti.cnr.it/
[5] http://wndomains.fbk.eu/wnaffect.html
[6] http://neuro.imm.dtu.dk/wiki/Sentiment_analysis

We have applied the polarity lexicons on the above mentioned modules and identified the polarity of the glosses. The polarity of a gloss (sentence) was calculated by computing the sum of the word level polarities (W) of the gloss (S_g) as in (1).

$$S_g = \sum_{i=1}^{n} W_i \quad (1)$$

Where, *i* indicate the number of words present in a gloss.

In Figure-1, we show the polarity computation procedure whereas in TABLE IV, the F-Measures for three modules with respect to all type of polarity lexicons are given. It is observed that, the results for positive polarity were found satisfactory when using Taboda's adjective list. Similarly, in case of identifying negative polarity, the Senti-WordNet performs well. In this particular study, we used all of the polarity lexicons independently one by one in order to identify the polarity of the glosses.

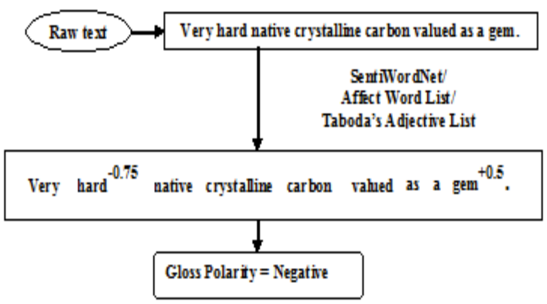

Fig. 1. Gloss level Polarity Computation Procedure.

TABLE IV. SENSE DISTRIBUTION (F-MEASURE) OF MODULES

Polarity Lexicons		Module-1	Module-2	Module-3
SentiWordNet	P	0.56	0.47	0.46
	N	0.27	0.15	0.31
Affect Word List	P	0.50	0.29	0.32
	N	0.19	0.44	0.25
Taboda's Word List	P	0.58	0.58	0.61
	N	0.25	0.11	0.11
P → Positive		N → Negative		

In Table IV, we can see that, in several cases, the polarity of the file context obtained via Module-1 is different from the polarities achieved via Module-2 and Module-3. Therefore, we have proposed two different approaches (Sequential and Combined) for sense disambiguation based on the polarity tagged descriptions for the medical events.

B. Sense Disambiguation

We introduce two approaches to extract the relevant sense of the medical events from its polarized descriptions provided by Module-1, Module-2 and Module-3. In the present task, the polarized glosses as extracted from Module-1, 2 and 3 are represented as FC_p, WD_p and DG_p, respectively.

Sequential WSD:

This approach helps us to extract the maximum number of sense based descriptions or glosses of the medical events from the modules. We pass each medical event along with its polarity through each of the modules one by one. If the polarity of an event is matched with the polarity of its corresponding gloss tagged by any of the modules, we considered that polarity and its description as a clue for identifying the correct sense of that event. The Figure-2 shows the sequential WSD approach and TABLE V shows the steps taken to develop the approach with an illustration using an example as shown in Figure-3.

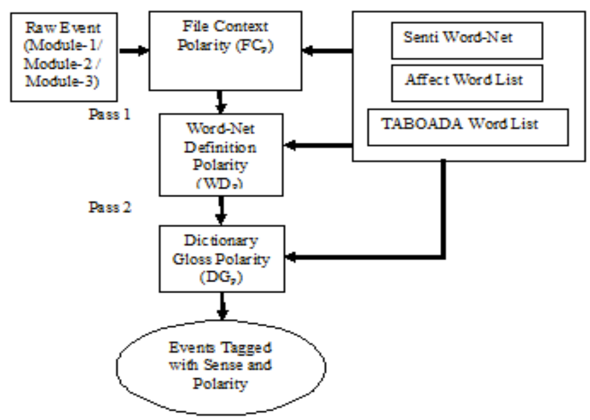

Fig. 2. Sequential WSD Approach Flowchart.

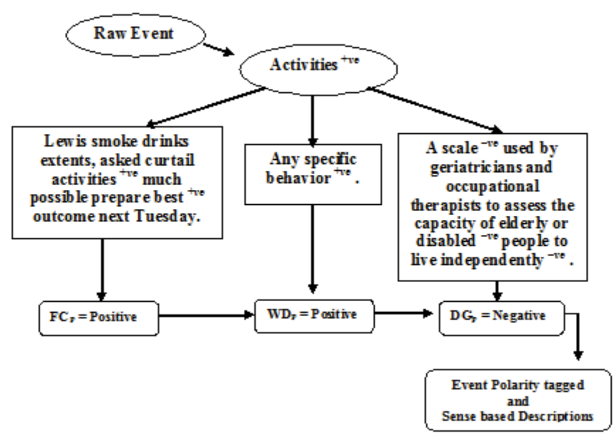

Fig. 3. Sequential WSD Algorithm Illustration With an Example.

Combined WSD:

In the case of our combined approach, we consider the glosses that are tagged with correct polarity by all of the modules. We compare the polarity of each of the glosses with the polarity provided for the medical event.

If polarity is matched with respect to the polarities assigned to all the glosses, we consider the respective glosses and the corresponding description for that medical event. Figure-4 shows the combined WSD approach and TABLE VI describes the steps of this approach. Lastly, an example is illustrated in Figure-5.

TABLE V. SEQUENTIAL WSD ALGORITHM

Step 1: The raw event (E_r) and event polarity (E_p).
Step 2: FC_p, WD_p and DG_p extracted with amalgamation of polarity lexicons.
Step 3: Begin the Polarity based comparison.
  Step 3.1: If (E_p == FC_p):
    E_r tagged with sense and polarity.
    Else:
    Move to Pass-1
  Step 3.2: In Pass-1, If (E_p == WD_p):
    E_r tagged with sense and polarity.
    Else:
    Move to Pass-2
  Step 3.3: In Pass-2, If (E_p == DG_p):
    E_r tagged with sense and polarity.
    Else:
    Exit()
Step 4: Repeat Step-1 to step-3 for all E_r.
Step 5: Apply Step-1 to step-4 for each module.

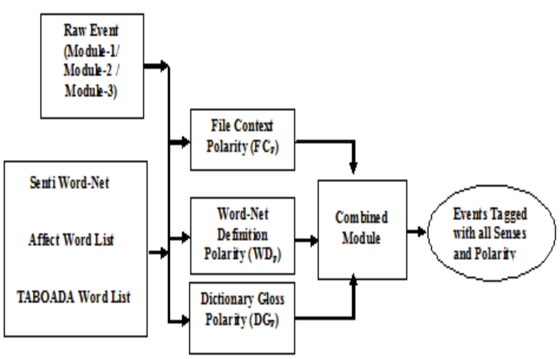

Fig. 4. Combined WSD Approach.

TABLE VI. COMBINED WSD ALGORITHM

Step 1: The raw event (E_r) and event polarity (E_p).
Step 2: FC_p, WD_p and DG_p extracted with amalgamation of polarity lexicons.
Step 3: Begin the Polarity based comparison.
  If (E_p == FC_p) and (E_p == WD_p) and (E_p == DG_p):
    Go to Combined step (Step-4)
  Else:
    Exit()
Step 4: If $FC_p \cap WD_p \cap DG_p \neq$ NULL
    E_r tagged with sense and polarity.
  Else:
    Stop()
Step 5: Apply Step-1 to step-4 for all E_r.
Step 6: Apply Step-1 to step-5 for each module.

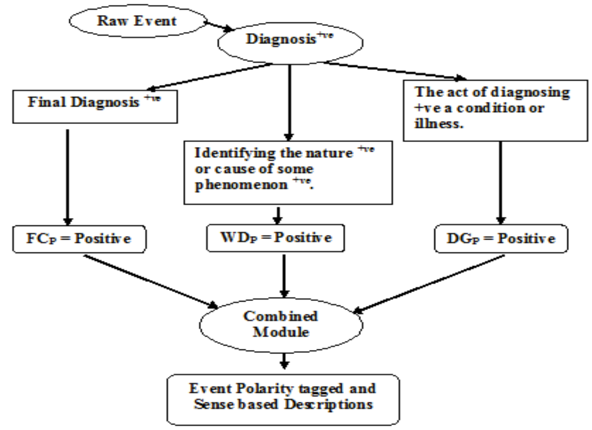

Fig. 5. Combined WSD Algorithm Illustration.

C. *Negation Handling*

While comparing the results, we observed that the extracted polarity did not match the polarity provided for the medical events. Therefore, we analysed the events that were not correctly identified by any of the approaches. It was observed that the events were controlled by the presence of negation words in their glosses. In order to improve the efficiency of the proposed approaches, we have considered the negation words from the negation word list containing 226 terms. Module-1, Module-2 and Module-3 were developed with 23, 16 and 18 unique negation words out of total number of 109, 107 and 102 occurrences in the corpus, respectively.

Next, these polarity lexicons were applied to the modules for handling the negations. TABLE VII illustrates the polarity distribution in the form of F-Measure after handling the negation and Figure-6 illustrates the procedure of computing with and without negations with an example.

TABLE VII. THE POLARITY DISTRIBUTIONS AFTER HANDLING NEGATIONS

Polarity Lexicons		Module-1	Module-2	Module-3
Senti WordNet	**P**	0.24	0.19	0.16
	N	0.08	0.19	0.13
Affect Word List	**P**	0.50	0.30	0.31
	N	0.19	0.44	0.24
TABOADA Word List	**P**	0.11	0.11	0.11
	N	0.05	0.20	0.07
P → Positive		N → Negative		

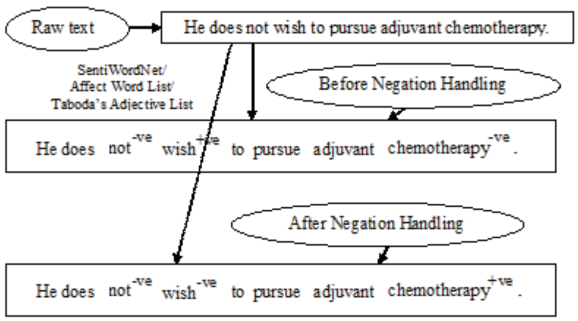

Fig. 6. Negation Handling with Polarity Lexicons.

V. DISCUSSION

A. Comparative Study

In this Section, we have done the comparative study of our proposed approaches in contrast to Lesk, a well known WSD algorithm for solving the sense disambiguation for general words [22]. Lesk WSD tries to guess the correct word sense by counting overlaps between dictionary definitions of the various senses. Lesk algorithm assumes that words in a given context tend to share a common topic. A simplified version of the Lesk algorithm is to compare the dictionary definition of an ambiguous word with the terms contained in its neighborhood terms. The Lesk algorithm simultaneously determines the meanings of all words individually in a given context, independent of the meaning of the other words occurring in the same context. It can hence benefit from post-processing using syntactic rules such as ‘verbs cannot appear immediately after an article’.

Further, it is found that the Lesk is very sensitive to the exact wording of definitions and therefore the absence of a certain word can radically changes the results. The accuracy also does not improve with length of context window or number of overlaps. Lesk algorithm is not suitable for the Clinical domain, due to lack of sufficient dictionary glosses necessary, to determine the distinction between related context senses.

All the three approaches have extracted the sense based descriptions of the medical events for all the modules. TABLE VIII illustrates the comparative analysis in the form of F-Measure with the help of Recall (R) and Precision (P) as in (2).

$$F - Measure = 2 * \frac{(R * P)}{(R + P)} \tag{2}$$

We have noticed that the Sequential WSD algorithm achieves F-measure of nearly 48% for extracting the sense based event description from the modules. On the other hand, it can be seen that the Combined and Lesk algorithms show a much lower F-measure of 27%.

TABLE VIII. COMPARATIVE ANALYSIS ON DIFFERENT TYPE OF WSD ALGORITHM

Module	**Different Types of Algorithm**		
	Sequential	***Combined***	***Lesk [22]***
Module-1	0.46	0.14	0.29
Module-2	0.47	0.26	0.29
Module-3	0.50	0.39	0.25

B. Aggreement Study

In this section, we focus onthe problem of determining the proper sense based descriptions of the medical events from lexical resources. Thus, we conducted a manual evaluation followed by an agreement study. In this task, the evaluation has been performed between two manual annotators with respect to each of the proposed approaches. The Cohen's kappa coefficient[7] based statistical approach has been considered in this agreement study. The Cohen's Kappa (k) value is measured by using equation (3) where (Pr(a)) is the Proportionate (Pr(a)) and (Pr(e)) is the Random agreement value.

$$k = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)} \tag{3}$$

In TABLE IX, the counts for agreed and non-agreed events for both the annotators are shown, where A and B represent two different annotators where as Y and N represent the agreed and non-agreed events, respectively.. Figure-7 shows the Kappa value for each of the modules.

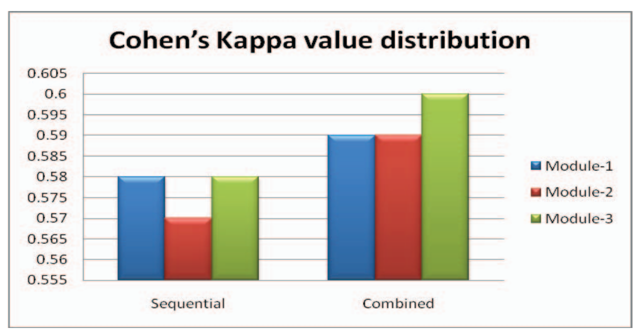

Fig. 7. Cohen's Kappa value Distribution for All Modules. *(figure caption)*

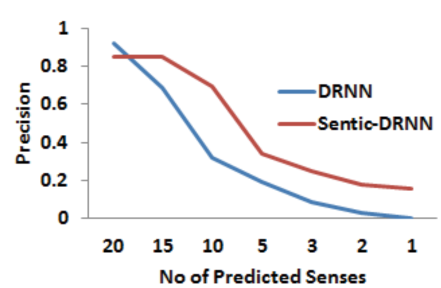

Fig. 8. Precison versus No of Senses using Sentic-DRNN.

[7] https://en.wikipedia.org/wiki/Cohen's_kappa

TABLE IX. NUMBER OF AGREED AND NON-AGREED EVENT SENSE BASED DESCRIPTIONS FOR MODULES 1,2 AND 3 AS VALIDATED BY ANNOTATORS A AND B.

			Sequential		Combined			
Module-1	**No. of Event**		**B**		**No. of Event**		**B**	
	765		**Y**	**N**	133		**Y**	**N**
	A	**Y**	658	28	**A**	**Y**	116	4
		N	25	54		**N**	5	8
Module-2	**No. of Event**		**B**		**No. of Event**		**B**	
	378		**Y**	**N**	134		**Y**	**N**
	A	**Y**	341	10	**A**	**Y**	117	4
		N	12	15		**N**	5	8
Module-3	**No. of Event**		**B**		**No. of Event**		**B**	
	217		**Y**	**N**	136		**Y**	**N**
	A	**Y**	199	4	**A**	**Y**	127	2
		N	6	8		**N**	3	4

C. Sentic WSD using Deep RNN

Lastly, we evaluate the proposed lexical resource for training a Deep Recurrent Neural Networks (DRNN) previously described in [24]. As an example, we consider three words ‘excess, band and shirt’ with corresponding ‘8,28 and 8’ different senses available in SemEval dataset. Hence, the task is to correctly classify a test sentence to one of (8+28+8=44) senses. This is a very challenging task as several senses are very similar for example “T-shirt” and “Sweat-shirt” are two different senses. A balanced training and test set of 1600 and 400 sentences respectively are used.

We train a DRNN with two convolution layers, a recurrent layer of 50 neurons and an output layer of 3 neurons for each word respectively. The DRNN is trained using back-propagation algorithm and each recurrent neuron is assigned a set of possible ‘word-senses’ corresponding to highly activated training sentences at that neuron. To determine the sense of a test sentence we rank the 50 recurrent neurons based on activation. The label of the test sentence is one of the possible ‘word-senses’ for the top neuron. Fig. 8 shows the precision versus maximum number of senses at a hidden neuron. It can be seen 92% of the test sentences are correctly classified to a hidden neuron containing its ‘word-sense’. However, some neurons contain up-to 20 other ‘word-senses’.

To reduce the ambiguity among senses at a particular neuron, we extract polarity concepts containing the three class words in *SenticWordNet* for all sentences. We now only consider ‘word-senses’ for which the training sentences have at least one concept common with the test sentence. It can be seen in Fig. 8, that in this way we can narrow down to a single sense in 20% of the test samples. Further, we can reduce the number of possible senses to 10 for a precision of 70% as against 15 senses predicted by DRNN.

VI. CONCLUSION AND FUTURE WORK

The main contribution of this paper is preparation of a lexical resource in the Clinical domain. The proposed approach helps the non-expert and expert group of people to increase their accessibility to the medical terms in their respective applications. The WME model is a productive resource to identify and extract the medical terms along with POS, polarity and sense based descriptions from a medical corpus. In future, we will be try to introduce some more features to improve the accuracy of the system. In the present task we have considered limited number of medical events. Hence, in future, we will enrich our system with a larger number of medical events along with more sense-disambiguated glosses. The MWE system will also result in better communication via web etc between expert and non-expert groups of people in the domain.

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