Clinical Text Analysis Using Machine Learning Methods

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***Abstract*—SemEval (Semantic Evaluation) is an annual workshop where attendees participate in a series of evaluations (competitions) of computational semantic analysis for natural language processing (NLP). The series evaluations include 10–20 tasks each year. In this paper we present our entry to the SemEval-2014 Task 7 on the Analysis of Clinical Text evaluation. The main aim of this task is to analyze large amounts of clinical data and to find the mentions of clinical disorders. This task consists of two sub tasks: a) named entity recognition i.e, identifying disorder concepts that belong to Unified Medical Language System (UMLS) semantic group; and b) normalization, i.e, mapping mentions of disorders to UMLS Concept Unique Identifier (CUI). In this paper, we present a supervised machine learning system for prediction of disorder named entities based on the conditional random field model. The data set provided by the Task 7 organizer was used to evaluate our model.**

***Index Terms*—natural language processing, semantic evaluation, clinical text analysis, conditional random fields**

I. Introduction

In the past few years, clinical natural language processing has received a critical acclaim for its role in revealing information trapped in the clinical texts. Accustoming and expanding natural language processing (NLP) techniques can open doors to better clinical studies and help patients understand their clinical records. SemEval [1] provides a forum, which is an annual workshop, where researchers can present their methods for evaluating semantic in various NLP Tasks, such as Cross-Level Semantic Similarity, Analysis of Clinical Text, and Sentiment Analysis in Twitter. In this paper, we discuss the tool we developed for named entity recognition that extracts disorder mentions after analyzing large amounts of clinical texts and mapping these mentions of disorders to UMLS CUIs [2]. Unified Medical Language System (UMLS) is a large collection of sources, including databases and a set of software tools which was designed and maintained by US National Library of Medicine. The UMLS Metathesaurus contains many *concept*s, each is given a Concept Unique Identifier (CUI). Many systems have been implemented in the past few decades to extract mentions of clinical disorders from large clinical texts [3]. But the main aim of SemEval Tasks is to measure the performance of semantic analysis by new tools. Among the various Tasks described by the SemEval [4], we have chosen Task 7 [5] to implement and evaluate the performance of our tool. Task 7 comprises of two tasks.

A. Task A

The first task is the recognition of mentions of concepts that belong to the UMLS semantic group disorders. Here are a few examples as stated in the SemEval 2014 Task 7 website [6]:

(A.a) The rhythm appears to be *atrial fibrillation*.
(A.b) The *left atrium* is moderately *dilated*.
(A.c) 53 year old man s/p *fall from ladder*.

In Examples (A.a) and (A.c), the terms *atrial fibrillation* and *fall from ladder* are in the disorder semantic group in UMLS. But the interesting thing in Example (A.b) is that, there are disorders present but are placed in different positions of the sentence (*left atrium ... dialated*). Besides our task is required to detect all disjoint parts of a disease.

B. Task B

The second task is to match the Concept Unique Identifiers (CUI) values to the disorders obtained from the first task. This process is called normalization process and the mapping of disorders to CUIs is limited to UMLS CUIs. The disorder entry examples in Task A above are mapped to the following CUIs:

(B.a) atrial fibrillation - C0004238; UMLS preferred term *atrial fibrillation*.
(B.b) left atrium...dilated - C0344720; UMLS preferred term *left atrial dilatation*.
(B.c) fall from ladder - C0337212; UMLS preferred term is *accidental fall from ladder*.

Example (B.a) represents the easiest cases. Example (B.b) represents instances of disorders as listed in the UMLS are best mapped using disjoint mentions. Example (B.c) is harder as one has to infer that the description is a synonym of the UMLS preferred term.

In this paper, we present a system based on a supervised Conditional Random Fields (CRF) model to perform the two tasks of SemEval Task 7 mentioned above. The system was applied to the data set of clinical reports provided by the SemEval organizers. Several measures were used to evaluate the system in two settings (strict and relaxed, to be explained

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in Section V). The results show that the system yield higher precision and F-score in relaxed setting than in the strict setting, and these measures are higher for Task B than for Task A.

II. Related Work

Document analysis falls in the area of text mining that involves algorithmic methods and domain knowledge of the documents being analyzed. Clinical text analysis is text mining applied to the domain of clinic documents. Due to its importance to medical and healthcare, many researchers have made great effort working on analysis of clinical text. A study on the potential of medical research and challenges using electronic medical records was presented in [7].

The research community of electronic medical records has created several forums to challenge researcher with various tasks to evaluate their methodologies. SemEval is one of the challenges presented to the participants to evaluate their methods on a wide range of tasks. The SemEval 2014 Workshop, for example, attracted 500 systems submitted by 185 teams for 10 tasks. The Task Description and System Description papers are given in a volume of the Proceedings [8]. Informatics for Integrating Biology and the Bedside (i2b2) is another natural language processing forum for electronic health records, that aims to provide a framework and resources for researchers to use existing data to investigate medical issues, and the participants build various corpora to support natural language processing [9], [10].

Several specific tasks for clinical text processing are the aims of ShARe/CLEF eHealth Lab. The tasks include named entity recognition and normalization of disorders, normalization of acronyms/abbreviations ans so on [11], [12]. Bodnari et al developed a supervised conditional random field model to extract disorder named entities from medical text [13]. Our work presented in this paper is most similar to [13], but the difference is that we applied various combinations on textual components for evaluation of our system while [13] only computed the system noun phrases, and the data sets are also different.

III. System Design

The system we developed is to extract various features for recognition of mentions of concepts in UMLS. A Conditional Random Fields (CRF) model [14] is built on the training data set and evaluated on the testing data set. We first describe the features to extract.

A. Features Developed

A sentence s is defined as a sequence of tokens $s = \cdots x_{-2}, x_{-1}, x_0, x_1, x_2 \cdots$. An n-gram is a n-token subsequence of s. For particular cases, an n-gram is called unigram or bigram if $n = 1$ or $n = 2$. We shall define features over n-gram centered at x_k.

1) Lexical Features: Features for unigrams (tokens) include following: type of token (letter, digit, punctuation, etc.), uppercase or lowercase if it is a letter, has sub-tokens or not (i.e. like they should contain upper case characters, it should be a digit which is capitalized and should be a punctuation. This features also includes correction of spellings

2) Syntactic Features: For every token identified in the clinical text, we include the base form of the word, POS (parts of speech) information, chunk information and named entity. We used the tool Genia Tagger [15], [16] to obtain these features. This tool takes a large amounts of data as input and outputs the desired features as discussed above.

Features expressed in this coding scheme are used in the Conditional Random Fields machine learning system. A sample is given in Table I. The columns are the word, base form, part-of-speech (POS) tag, chunk tag and named entity (NE) tag. Notice that the chunk tags show the terms are expressed as B-NP (noun phrase), I-VP (verb phrase), etc.

TABLE I
SYNTACTIC FEATURES

Word	Base	POS tag	Chunk tag	NE tag
He	He	PRP	B-NP	0
reckons	reckon	VB2	B-VP	0
the	the	DT	B-NP	0
current	current	JJ	I-NP	0
account	account	N	I-NP	0
deficit	deficit	NN	I-NP	0
will	will	D	B-VP	0
narrow	narrow	VB	I-VP	0
to	to	TO	B-PP	0
only	only	RB	B-NP	0
*	*	SYM	I-NP	0
1.8	1.8	CD	I-NP	0
billion	1.8	CD	I-NP	0
in	in	IN	B-PP	0
September	September	NN	B-NP	0
.	.	.	O	0

3) CRF Features: We model the problem of recognizing disorder terms as a supervised classification task with three labels: B-Disorder, I-Disorder, and O. The B-I-O coding refers to **b**egin, **i**nside, and **o**utside. A feature expressed with multi-tokens is encoded with the B-I-O scheme. Given a label L, the first token is B-L, the next token is I-L, and tokens that do not have this feature is O. In our task, the label L is Disorder. With all these rich features, we train our model using CRF [17]. A sample input format for the CRF tool is shown in Fig. 1.

4) UMLS features: Our main aim is to identify the disorders from two sources: cTakes [18] and MetaMap [19]. We first extract the information in the clinical text by cTAKES. Then MetaMap is used to identify the semantic groups from the information obtained from cTAKES.

TABLE II
UNIFIED MEDICAL LANGUAGE SYSTEM FEATURES

	Phrase from MetaMap	Concept in SNOMED CT	Semantic Type	CUI
1	Pericardial effusion	Pericardial effusion	Disease or Syndrome	C0031039
2	Severe symmetric left ventricular hypertrophy	Left Ventricular Hypertrophy effusion	Disease or Syndrome	C0149721
3	With increased SOB	SOB (Dyspnea)	Sign or Syndrome	C0013404

```
791     791 CD  B-NP    O
C0012621   C0012621    NN  I-NP    O
:  :   :   O   O
Discharge  Discharge   NNP B-NP    O
(  (    (  O   O
Body    Body   NNP B-NP    O
Body    Body   NNP I-NP    O
Substance  Substance   NNP I_NP    O
]  ]   )   O   O

791     791 CD  B-NP    O
C0030685   C0030685    NN  I-NP    O
:  :   :   O   O
Discharge  Discharge   NNP B-NP    O
(  (   (   O   O
Patient    Patient  NNP B-NP    O
Discharge  Discharge   NNP B-NP    O
)  )   )
]  ]   )   O   O
Health   Health  NNP B-NP    O
Care     Care    NNP I-NP    O
Activity   Activity      NNP I-NP  O
]  ]   )   O   O
```

Fig. 1. Input format of a CRF tool

The UMLS features are given in Table II. In this table, SNOMED CT refers to **S**ystematized **N**omenclature **O**f **Med**icine **C**linical **T**erms [20], that is a collection of medical terms considered the most comprehensive medical and healthcare terminology collection in the world.

5) Wiki features: In the given data sets there contains some noun-phrases, in which case we use wikipedia category information to classify them. These categories (semantic groups) include disorders, body parts, living beings, chemicals, phenomenon, object, geographical location, devices and others.

IV. TOOLS USED

Three tools are used in our experiments: CRF++, MetaMap, and cTakes. Brief descriptions of these tools are given below.

A. CRF++

Conditional Random Fields are a class of statistical modeling methods often applied in data mining and machine learning. It has been used in various domains such as part of speech tagging and natural language processing. We used the tool CRF++ [21] for building our model. Each feature in CRF++ has a weight that gives the strength of that feature for the proposed label. The weight is

- 1: a good group between the feature and the proposed label
- -1: a negative group between the feature and the proposed label
- 0: the feature has very small or no impact on the identity of the label

Before feeding the training data and testing data to CRF++ they should be arranged according to the format. In our case the format should be disorder followed by it's CUI value, punctuation marks and some other features like POS tagging, chunk information, etc. The more number of features the more accuracy will be gained.

B. Metamap

MetaMap [19] is a tool for identifying Metathesaurus concepts. MetaMap has a natural language processing (NLP) technique and is used worldwide in industry and academia. It provides access to the concepts in UMLS. It is mainly developed to improve biomedical text retrieval. It not only provides Metathesaurus from biomedical text but also gives the POS tagging and various other features. The main feature we will obtain from this is the CUI values of each disorder.

C. cTakes

cTakes [18] is a NLP system for information extraction from medical records and clinical texts. It takes some clinical text as some input and it gives various types of clinical disorders including the UMLS disorders. This is same as MetaMap but it gives some more features like shallow parsing and relation extractor. In general what we do is we take the features obtained from MetaMap and combine them with cTakes. In particular they both give the same CUI values for a particular set of disorder mentions.

V. RESULTS

We conducted experiments running our system on the text data set provided by the SemEval organizers. In this section, we describe the data set, evaluation measures, and the results of the evaluation results. We also briefly compare our results with the one in [13] that also used the conditional random fields methods to extract disorder named entities from clinical text.

A. Data

The data provided by the SemEval organizers consists of the 300 clinical reports (documents) from the US Intensive Care. The data can be obtained from the PhysioNet [22]. The provided data included two sets, ie., the training data of 200 documents and the testing data of the remaining

100 documents. Furthermore, these two data sets are further divided into four subsets: Discharge Summary [23], ECG, Echo and Radiology. Each of this subsets contains *text* and *pipe* files. Text files are complete medical records of patients and pipe files are CUI's of the disorder mentions and the starting and ending positions of that disorders.

The training and testing data sets are summarized in Tables III(a) and III(b), respectively.

TABLE III
COUNT AND AVERAGE SIZE OF EACH TYPE OF CLINICAL NOTE

(a) Training data set

Type of Report	Count (%)	Average Size (bytes)
Discharge Summary	61 (30.7%)	7,561
ECG	54 (27.1%)	285
Echo	42 (21.1%)	2,235
Radiology	42 (21.1%)	1,941

(b) Testing data set

Type of Report	Count (%)	Average Size (bytes)
Discharge Summary	76 (76.0%)	7,561
ECG	0 (0.0%)	—
Echo	12 (12.0%)	2,246
Radiology	12 (12.0%)	1,717

B. Evaluation Measures

The evaluation measures are precision, recall, and F-measure, defined as

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F\text{-}measure = \frac{2 \times Precession \times Recall}{Precession + Recall}$$

where TP is the count of true positive (a disorder is identified in the same span), FP the count of is false positive (a disorder is identified in an incorrect span), and FN is the number of false negative (system failed to identify a disorder-span).

Accuracy is used as the evaluation metric for the normalization task. It is defined as follows:

$$Accuracy = \frac{CORRECT}{TOTAL}$$

These measures were computed in out experiments under two settings: *Strict* where annotations remain intact, and *Relaxed* where annotations were deleted by the system.

C. Structure of Text File

This is the structure of a text file which is provided in the given reports. There will be many number of text files in each report. It contains the records of many patients from all over across the world. This file contains many disorders to be identified. Before identifying disorders we need to bring together all the files into a single file so that it will be easy for identifying disorders. A sample text file is given in Fig. 2.

```
[***] |||| [] |||| [***] |||| DISCHARGE_SUMMARY ||||
      [2015-03-24 00:00:00] |||| |||| |||| ||||
Admission Date: [**2015-03-17**]
Discharge Date: [**2015-03-24**]

Date of Birth:  [**1974-10-03**]  Sex:  F

Service: Neurosurgery

HISTORY OF PRESENT ILLNESS: The patient is a 41-year-old
female with complaints of headache and dizziness. In
[**2015-01-14**], the patient had headache with neck
stiffness and was unable to walk for 45 minutes. The
patient also had a similar episode a year and a half ago
where she had inability to walk without pain. She had a
headache at that time which was relieved with Tylenol.

PAST MEDICAL HISTORY:  Hypothyroidism.

ALLERGIES:  Penicillin and Bactrim which causes a rash.

MEDICATIONS:  Levoxyl 1.75 mg.

PHYSICAL EXAMINATION:  On physical examination, her blood
pressure was 104/73, pulse 79. In general, she was a woman
in no acute distress.  HEENT:  Nonicteric. Pupils are
equal, round, and reactive to light. Extraocular movements
are full. Pharynx is benign. Tongue midline. Neck is
supple. Chest was clear to auscultation. Cardiac: S1, S2,
regular, rate, and rhythm.  Abdomen is soft, nontender,
nondistended, negative bruits. Extremities: No clubbing,
cyanosis, or edema. Palpable pulses. Gait was steady.
```

Fig. 2. Structure of a text file for discharge summary

D. Structure of Pipe File

The pipe files should be in the following format.

report_name || annotation_type || cui || char start || char end

we have to identify these files in such a way that it should contain report name followed by annotation type followed by CUI value. Char start and char end indicate the starting and ending character of a disorder in the text file. Fig. 3 shows a sample pipe file.

```
00098-016139-DISCHARGE_SUMMARY.txt||Disease_Disorder||C0018681||330||338
00098-016139-DISCHARGE_SUMMARY.txt||Disease_Disorder||C0012833||343||352
00098-016139-DISCHARGE_SUMMARY.txt||Disease_Disorder||C0018681||392||400
00098-016139-DISCHARGE_SUMMARY.txt||Disease_Disorder||C0151315||406||420
00098-016139-DISCHARGE_SUMMARY.txt||Disease_Disorder||CUI-less||429||443
00098-016139-DISCHARGE_SUMMARY.txt||Disease_Disorder||CUI-less||536||553
00098-016139-DISCHARGE_SUMMARY.txt||Disease_Disorder||C0030193||562||566
00098-016139-DISCHARGE_SUMMARY.txt||Disease_Disorder||C0018681||579||587
00098-016139-DISCHARGE_SUMMARY.txt||Disease_Disorder||C0020676||658||672
00098-016139-DISCHARGE_SUMMARY.txt||Disease_Disorder||C0015230||725||729
00098-016139-DISCHARGE_SUMMARY.txt||Disease_Disorder||CUI-less||888||902
......
```

Fig. 3. Structure of a pipe file for discharge summary

E. Results

We conducted some experiments using the system with various combinations of text-processing components, and the results are given in Table IV.

TABLE IV
PERFORMANCE OF SYSTEM COMPONENTS COMBINATION

Task / Type	Measure	Components and Combinations					
		a	a+b	a+b+d	c	a+b+c	a+b+c+d
Task A / Strict	Precision	0.084	0.480	0.563	0.698	0.517	0.713
	Recall	0.076	0.447	0.384	0.151	0.586	0.650
	F-score	0.080	0.463	0.457	0.248	0.549	0.680
Task A / Relaxed	Precision	0.703	0.704	0.872	0.904	0.739	0.895
	Recall	0.667	0.658	0.608	0.194	0.816	0.796
	F-score	0.684	0.680	0.716	0.319	0.776	0.843
Task B / Strict	Accuracy	0.059	0.391	0.3	0.144	0.526	0.57
Task B / Relaxed	Accuracy	0.782	0.874	0.781	0.956	0.897	0.876

In the table, the components are:

a – data sets with MetaMap annotation
b – normalization of data set
c – rule based annotation
d – pre-processing

where *normalization* is the process of matching/mapping the CUI values to the disorders obtained from the Task A, and *pre-processing* is the part where we process the preliminary data set by making a structure out of the raw data by splitting the data into sentences.

The results show that using the data set with MetaMap annotation alone (Strict setting) have very low values on all the measures, where combined with other components generated reasonable measure.

Our system yielded comparable measures as in [13] given in Table V that has only computed the system noun phrase span overlap with the gold standard, but has higher recall and F-score values for most component combination cases, and a bit lower precision measure.

TABLE V
EVALUATION RESULTS IN [13]

Setting	Precision	Recall	F-measure
Strict	0.814	0.473	0.598
Relaxed	0.964	0.563	0.711

VI. CONCLUSION AND FUTURE WORK

In summary, we have shown that a system with multi-class entities is capable of gaining reasonable performance in the clinical domain without compromising performance in other classes. Clinical documents often contain mentions of disorders and associated quantitative values (e.g.dosage, serum concentrations). We have used many existing tools in developing our system features. Empirical results suggest that if a disorder mention is correctly identified by Metamap, then its mapping to a CUI value provided by this system is highly likely to be correct.

There is much work to be done in the area of representing temporal information in clinical records [24]. Better understanding of event semantics, such as whether a disease is chronic or acute, or typical duration for a treatment, may help constrain relations.

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