Feature engineering combined with machine learning and rule-based methods for structured information extraction from narrative clinical discharge summaries

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ABSTRACT

Objective A system that translates narrative text in the medical domain into structured representation is in great demand. The system performs three sub-tasks: concept extraction, assertion classification, and relation identification.

Design The overall system consists of five steps: (1) pre-processing sentences, (2) marking noun phrases (NPs) and adjective phrases (APs), (3) extracting concepts that use a dosage-unit dictionary to dynamically switch two models based on Conditional Random Fields (CRF), (4) classifying assertions based on voting of five classifiers, and (5) identifying relations using normalized sentences with a set of effective discriminating features.

Measurements Macro-averaged and micro-averaged precision, recall and F-measure were used to evaluate results.

Results The performance is competitive with the state-of-the-art systems with micro-averaged F-measure of 0.8489 for concept extraction, 0.9392 for assertion classification and 0.7326 for relation identification.

Conclusions The system exploits an array of common features and achieves state-of-the-art performance. Prudent feature engineering sets the foundation of our systems. In concept extraction, we demonstrated that switching models, one of which is especially designed for telegraphic sentences, improved extraction of the treatment concept significantly. In assertion classification, a set of features derived from a rule-based classifier were proven to be effective for the classes such as conditional and possible. These classes would suffer from data scarcity in conventional machine-learning methods. In relation identification, we use two-staged architecture, the second of which applies pairwise classifiers to possible candidate classes. This architecture significantly improves performance.

INTRODUCTION

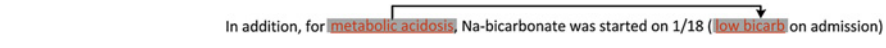
Digitization of medical records is a growing and inevitable trend with the increasing adoption of information technology in hospitals. For physicians, it would be extremely useful if relevant information could be extracted from medical records and stored in structured form. With structured representation of medical concepts, clinical assertions, and their relations, physicians could quickly access patients' medical records for clinical decision making.

We built a complete system that performs the three tasks[1] defined by the i2b2 2010 challenge: concept extraction, assertion classification, and relation identification. The concepts, called named-entities, consist of *medical problem*, *treatment*, and *test*. Assertions denote the status of a medical problem. A medical problem is to be associated with one of six assertion classes: *present*, *absent*, *possible*, *conditional*, *hypothetical*, and *not_associated_with_the_patient*. A relation exists between a *medical problem* and a concept. The relations to be identified are TrIP, TrWP, TrCP, TrAP, TrNAP, TeRP, TeCP, and PIP. TrIP indicates that the treatment improves the medical problem, TrWP that the treatment worsens the problem, TrCP that the treatment causes the problem, TrAP that the treatment is administered for the problem, TrNAP that the treatment is not administered because of the problem, TeRP that the test reveals the problem, TeCP that the test is conducted to investigate the problem, and PIP that the first problem indicates the second problem.

An example illustrating the three tasks is shown at the bottom of the page. The phrases 'metabolic acidosis' and 'low bicarb,' underlined and in red, belong to *medical problem*, the gray background color means *present*, and the arrow indicates PIP between 'metabolic acidosis' and 'low bicarb.'

The system is evaluated using the open published data provided by the i2b2 organizer. The training set includes 349 labeled discharge summaries with 27 837 concepts, 11 968 assertions, 5264 relations, and 827 unlabeled discharge summaries. The test set consists of 477 labeled discharge summaries with 45 009 concepts, 18 550 assertions, and 9070 relations.

Our contribution in this paper is threefold. First, after establishing a processing framework, we have invested significant effort in feature engineering to achieve the best performance for the three tasks. Second, both machine learning and rule-based methods were incorporated in the system. In assertion classification we used, as features for machine learning-based classifiers, carefully designed values that denote the classification result by a rule-based subsystem and its confidence, and thus combined the advantages of the two



approaches. Third, we developed a new concept extraction algorithm, which dynamically switches two separate conditional random fields (CRF) models[2] by using a dosage-unit dictionary. The two models, Model_medication and Model_other, are applied to different sets of sentences that are easily recognized using the dosage-unit dictionary.

The whole system consists of three sub-systems: (1) a concept extractor that dynamically switches two CRF models,[2] Model_medication and Model_other, to extract concepts; (2) an assertion classifier that combines a rule-based classifier and four machine learning classifiers[3] to decide a category for assertion; and (3) a relation identifier that combines four machine learning classifiers with discriminating features[4 5] to identify relations. The experiment results show that our system demonstrates state-of-the-art performance in all three tasks.

BACKGROUND

In the medical domain, there has been extensive work on natural language processing (NLP) tools and information extraction over the past 20 years. Spyns[6] surveyed medical language processing and listed NLP application systems and tools in the medical domain, such as LSP-MLP[7] and MEDLEE.[8] Meystre *et al*[9] provided a comprehensive review of information extraction from electronic medical records since 1995. Szolovits[10] built a medical lexicon into the Link Grammar Parser (LGP) to obtain more accurate syntax information and applied it to emergency department notes. The recent trend in event/relation identification in the bio-medical domain was surveyed in Ananiadou *et al*.[11]

There have been several reports directly related to our work. Sibanda[12] presented a category and relationship extractor (CaRE) that extracts concepts, classifies assertions, and identifies relations, and reported that the rule-based classifier outperformed the statistical classifier when the training data available were limited. Jagannathan *et al*[13] evaluated the effectiveness of commercial NLP engines for extracting medication information concerning medication name, strength, route, and dosing frequency. Their work was based on 2000 medical records. Furthermore, in recent years, several challenge tasks using medical records have been devised. In 2007, a shared task on multi-label classification of radiology reports[14] was organized, in which 45 ICD-9-CM codes were chosen as the class labels. The i2b2 organizer has held a series of challenges since 2006. The tasks were diverse, such as de-identification[15] and smoking assertion[16] of discharge summaries (2006), multi-label classification of obesity and co-morbidities from discharge summaries[17] (2008), medication extraction of seven labels from discharge summaries[18 19] (2009) and concepts, assertions, and relations extraction in clinical text (2010). This paper deals with the 2010 challenge and uses the same dataset for evaluation and comparison. Similarly to Sun *et al*[20] and Minard *et al*[21] in the challenge, we followed the ideas of NegEx[22] and ConText[23] for our rule-based component in the assertion task. However, the rule-based component is only part of our system. The output of the rule-based system is not used as the final result but is presented to machine learning-based classifiers, with the final judgment made through voting by five classifiers.

METHODS

Figure 1 provides an overview of the system. Figure 2 shows both the general and detailed flow diagrams of the overall system. All of the dictionaries used in our system are available at http://research.microsoft.com/en-us/projects/ehuatuo/default.aspx.

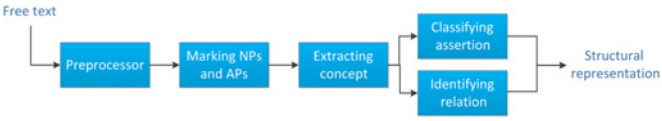


Figure 1 A flow diagram of the overall system.

Pre-processing sentences

This step reformats sentences so that standard NLP tools can be applied. This includes removal of itemized symbols (eg, '1)'), replacement of symbols with corresponding expressions (eg, 'r/o' by 'rule out'), deletion of dots, etc.

Marking noun phrases and adjective phrases

Because concepts are expressed in the form of NP (noun phrase) or AP (adjective phrase), NPs and APs are marked by an NLP tool (SharpNLP[4]) as candidates of concepts. SharpNLP is an open source NLP tool originally developed for processing of newspaper articles. Since discharge summaries show peculiar linguistic characteristics not common in newspaper articles, we made several modifications. Furthermore, since only the boundaries of NP/AP phrases are relevant to concept extraction, their internal structures, which are serious causes of ambiguity in other NLP applications, are ignored. Ambiguities between the gerund and the adjectival reading of a verb in the progressive form, for example, are suppressed from being generated. We also mark only the smallest phrases in complex NPs and APs as candidates of concepts. Only exceptions are NPs that contain prepositional phrases that indicate organ/body part.[24 25] We also modified SharpNLP to deal with NPs inside peculiar expressions, such as '2019-06-14 10:30 AM BLOOD CK-MB - 3 cTropnT - 0.05 *.' We first detect the date and time expression at the beginning, which is often followed by pairs of NPs (a test and its value).

Concept extractor

Concepts in the i2b2 challenge belong to the three classes, *medical problem*, *treatment*, and *test*. However, careful examination of the training corpus reveals that there is a distinct subclass of *treatment*, which we call *medication*. Not only is the frequency of the subclass very high but also a sentence containing the subclass often has a specific style as a sentence. Out of randomly selected 300 *treatment* concepts in the training set, 197 concepts belong to this subclass. Sentences with *medication* concepts in them are often telegraphic, and do not follow the ordinary English syntax. Instead, they often have a fixed semantic pattern such as [Medication] [digits] [dosage-unit] [mode]. 'Folic acid 1 mg p.o. daily' is a typical example. These telegraphic sentences are interspersed freely with ordinary sentences. Since they are very different from ordinary sentences, we have to provide a concept-extraction module specifically constructed for them.

In order to construct a special extraction model for these sentences, we need training data, which i2b2 does not provide. A simple dictionary-based concept extraction method does not work for *medication*, since the class of *medication* has an abundance of lexical variances. For example, term expressions in a medication dictionary (eg, UMLS medication brand name dictionary) are canonical, while their colloquial equivalents frequently appear in discharge summaries. Furthermore, a medication name often has synonyms, abbreviations, trade names, systematic (chemical) names, and various combinations. For example, 'morphine' has a systematic name (morphine), two trade names (Mscontin and Oramorph), synonyms (MS Contin, Avinza, Kadian, Oramorph, and Roxanol), an abbreviation (MSIR), and various combinations such as 'morphine (Oramorph).' Furthermore, unlike the other

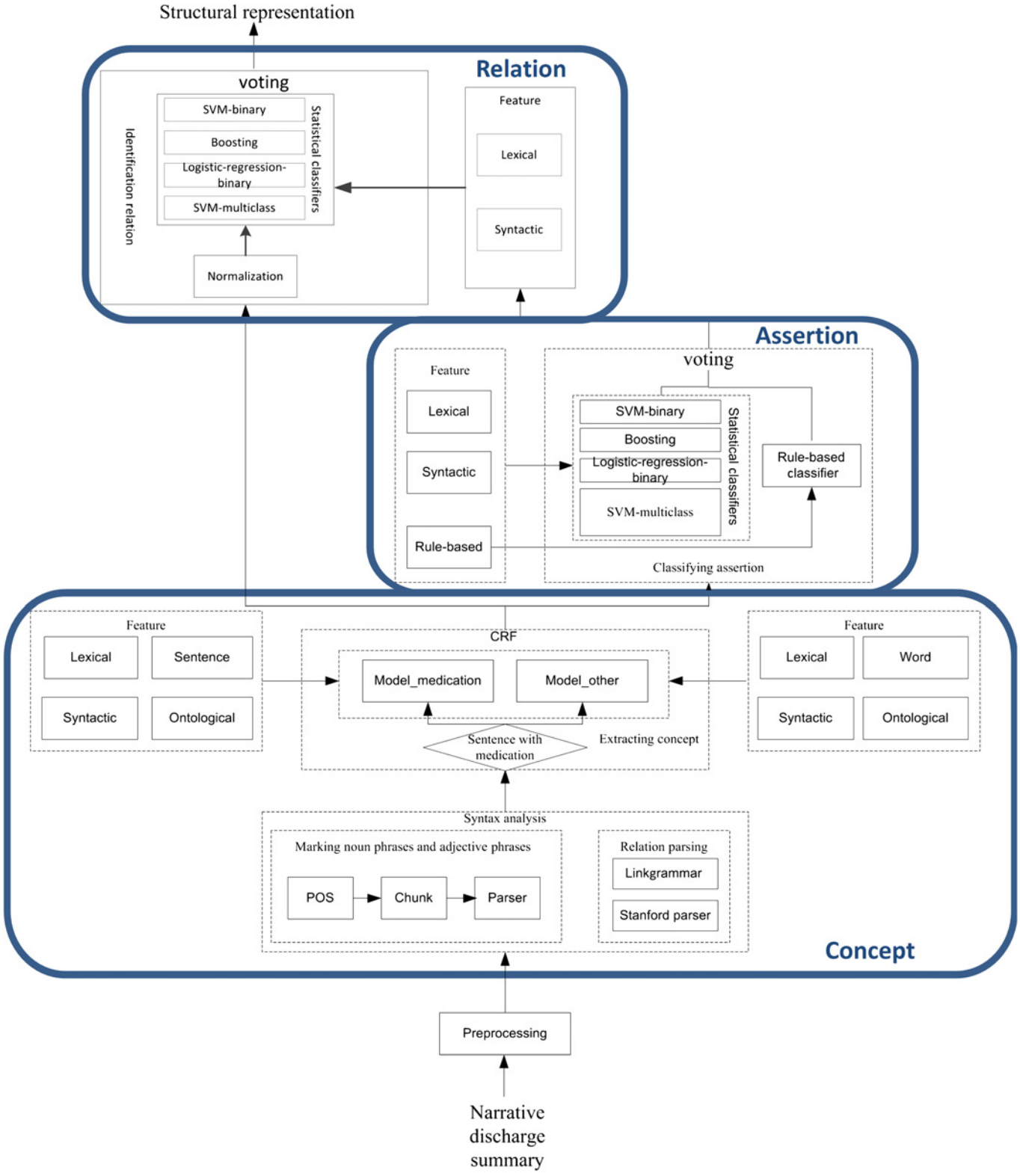


Figure 2 A detailed overall flow chart of the system. CRF, conditional random field; POS, part of speech; SVM, support vector machine.

classes, new medications appear regularly. It is very difficult, if not impossible, to construct a dictionary that covers all these medication names and keep it up to date.

Instead of expressions in *medication*, we use expressions of dosage-unit to detect telegraphic sentences. The same set of dosage-units such as *ml*, *gr*, *m-grams*, etc, is used for a wide range of different types of *medication* and they constitute a closed set. Whenever *medication* occurs in a telegraphic sentence, it is accompanied by a dosage-unit. In other words, the occurrence of a dosage-unit signals that the sentence is telegraphic, so we can identify a telegraphic sentence by just looking for dosage-unit expressions. These characteristics of dosage-unit expressions and telegraphic sentences allow us to construct a training set of telegraphic sentences. At the actual processing phase, we switch

the concept extraction model from the model for ordinary sentences to the model for telegraphic sentences when a dosage-unit expression is found.

While we construct a dictionary for standard dosage-units from UMLS, SNOMED_CT, and the training data, we use simple elastic matching for dictionary look-up instead of exact matching. That is, each word in a sentence, if it literally intersects with a word in the dictionary of dosage-units, is considered as a dosage-unit. This simple elastic matching works very well. Among 8894 expressions in the test data retrieved by this elastic matching, only 130 are not dosage-unit expressions. The exact matching can only identify 6835 expressions for the same test data. We use several dictionaries for concept extraction, other than the dosage-unit dictionary. When an expression matches an entry in one of these dictionaries, we assign specific features that indicate the dictionary in which the match is found. Since each dictionary corresponds to a specific class of concepts, these features are effective cues for machine learning-based classifiers. In the following, we will briefly describe each of the dictionaries, how the dictionaries are constructed, and how the features from the dictionary are used for the two concept extractors, Model_medication (for telegraphic sentences) and Model_other (for ordinary sentences).

Building dictionaries for concept extractors

It is well known that a dictionary can be used to facilitate concept extractors or named-entity recognizers. However, a dictionary alone does not result in high performance, due to the incomplete coverage of a dictionary (low recall) and the existence of ambiguous terms (low precision). Instead, we use information from dictionaries as features for CRF-based extractors to overcome the deficiencies of the dictionary-only approach. Four dictionaries are constructed from the following current resources.

UMLS dictionary

The UMLS dictionary contains *medical problem* that is subclassified into 14 semantic types, *treatment* into six types, and *test* into six types.[25]

MeSH dictionaries

Every phrase in MeSH belongs to one semantic type, which is denoted by an ID of alpha-numeric characters.[24] The MeSH vocabulary branches with identifiers with 'B' and 'C' as the initial character, those with 'D' as the initial character, and those with 'E' as the initial character correspond to *medical problem*, *treatment*, and *test*, respectively.

Medication dictionary

The medication dictionary is constructed from UMLS[21] and SNOMED_CT.

Head-noun dictionaries

Head-noun dictionaries[26 27] are built by extracting the head nouns of the three categories (ie, *medical problem, treatment,* and *test*) from UMLS dictionaries and the training data.

Each category in the dictionaries is used as a binary feature in our feature vector representation. When a NP or AP contains a term in a specific category of one of these four dictionaries, the corresponding feature will be set to 1. Otherwise, it is set to 0. In total, we have 10 binary features (ie, UMLS: 3, MeSH: 3, medication: 1, head-noun: 3).

Creating features

Five sets of features are used in our CRF-based[28 29] extractors: lexical context, syntactic context, ontological, sentence, and word features. Table 1 shows these five feature sets. Table 2 lists the selected feature sets for both Model_medication and Model_other. Although most of the features are those commonly used in named-entity recognizers and are self-evident, the features that we specifically introduced for our extractors are described below.

Pattern matching (CF1)

Some items in discharge summaries are expressed in highly stylized ways. For example, in the section describing the status of patients, a sentence such as '2018-10-25 11:15 AM BLOOD WBC - 18.3 * RBC - 3.42' may appear. In this sentence, a pattern of 'test - digit' appears twice, and the same pattern appears repeatedly in other sentences as well. These patterns, which are beyond ordinary English syntax, are treated by a pattern matching module. Once a candidate for a NP or AP is recognized as part of such a pattern, the candidate is given a corresponding feature and used by the CRF-based extractors.

Word normalization (CF2)

We normalize the words containing numbers and symbols.[30] We replace decimals with *Num*, telephone number like 319-335-9253 with *PhoneNum*, date like 01/01/2011 with *Date*, and time like 10:20am with *Time*. We also add word stems as features.

N-character-prefix-and-suffix (CF3)

In the medical domain, concepts with the same topics often share the same prefix and/or suffix.[31 32] For instance, the words 'pharmacotherapy' and 'chemotherapy' have the same suffix 'therapy,' which indicates that they both correspond to treatment. Therefore, we extract all possible N-character ($2 \leq N \leq 7$) prefixes and suffixes as features to be used for concept extraction. For example, from the word 'angiograph,' we extract a total of 14 features (prefix: 'a,' 'an,' 'ang,' 'angi,' 'angio,' 'angiog,' and 'angiogr'; suffix: 'h,' 'ph,' 'aph,' 'raph,' 'graph,' 'ograph,' and 'lograph').

Table 1 List of various features for the concept task

Category	Features
Lexical context features	The target itself (n-gram)
Syntactic context features	The POS
	The phrases of NPs and APs
Ontological features	UMLS-based dictionary matching
	MeSH-based dictionary matching
	Medication dictionary matching
	Head-noun dictionary matching
Sentence features	The sentence with a dosage-unit or temporal adverb (eg, twice daily or q4h)
	The sentence with numerals before dosage-units
	The sentence containing a drug name before a numeral
	The sentence with characteristics such as [the phrase] [numeral] [dosage]
	The sentence with a drug name followed by an alternative drug name in parentheses, eg, fosamax (alendronate)
Word features	Word capitalized
	Entire word capitalized
	Word abbreviation
	The phrase before the numerals
	Assertion word
	Body word
	Pattern matching
	Word normalization
	N-character-prefix-and-suffix
	Word clustering

AP, adjective phrase; NP, noun phrase; POS, part of speech.

Table 2 Selected feature sets for both Model_medication and Model_other

	Lexical context	Syntactic context	Ontological	Sentence	Word
Model_medication	x	x	x	x	
Model_other	x	x	x		x

x Indicates that the dictionary in each column exists for the corresponding category.

Word clustering (CF4)

Jargon (eg, prn), abbreviations (eg, CT), and rare terms (eg, bibasilar) are used in discharge summaries. Clustering words into classes can aggregate words with common properties and alleviate the problems caused by data scarcity. We used an unsupervised word clustering based on distributional and morphological information.[33] As morphological information, we used the dictionary of medical suffixes.[31] All the data released by the i2b2 organizer are supplied to the algorithm.[33] After clustering, every word is associated with a class. We have a feature for the word class in our feature representation. The number of clusters (and thus the number of the values for the word class feature) is predefined in our clustering algorithm. We use various configurations of the cluster number, that is, 50, 100, 200, 400, 600, and 800.

Training CRF models for extracting concepts and matching corresponding types

The linear-chain CRF[28] is used as a framework for the two concept extractors. The standard Begin/Inside/Outside (BIO) tags were used to mark concept boundaries.

Assertion classifier

In the i2b2 challenge, for assertion classification, a lot of groups used rule-based methods. Sun *et al*[20] proposed a method based on NegEx[22] and ConText[23] algorithms, and used the SNOMED_CT dictionary to match self-asserted concepts such as 'afebrile.' Minard *et al*[21] proposed a method combined of a rule-based method and machine learning. The rule-based method is an extension of NegEx. The support vector machine technique (SVM) is used for machine learning. We also used the hybrid approach combining one rule-based classifier with four statistical classifiers[34] by voting. In statistical features, we used syntax features (2-gram LGP syntax, verb) and section names.

Generating the dictionary for the rule-based classifier

Considering the limited availability of training data and motivated by Sibanda's work,[12] we put emphasis on the manual construction of an effective dictionary such as NegEx[22] and ConText.[23] Careful examination of the training data reveals that the appearance of a particular clue word in the neighborhood of the *medical problem* concept strongly signifies the assertion status of the concept. The scope of the neighborhood depends on a clue word which should precede or succeed the *medical problem* in a sentence for it to affect the assertion status of the *medical problem*. The neighborhood is normally the whole sentence, but the existence of particular words (eg, but) splits the eligible neighborhoods in a sentence. An entry in the keyword dictionary consists of a clue word, the assertion class that the word implies, and the scope of neighborhood (Preceding, Succeeding, or Any). Another list of words that delimit the scope was also provided. An example of description in the dictionaries is shown in table 3. The underlined word is the matched term in the dictionary and the italic word is the *medical problem* concept in the example column. The number of the entries in the dictionary is shown in table 4. All the dictionaries are available online.

Classifying assertions by the rule-based classifier

Assertion classification is the task of classifying an occurrence of *medical problem* into one of the six categories: *not_associated_with_the_patient*, *hypothetical*, *conditional*, *possible*, *absent*, and *present*. When one concept can be classified into more than one category (eg, *not_associated_with_the_patient* and *present*), the category with the highest priority should be selected as the final choice. The above six categories are listed in decreasing order of priority. However, the rule-based classifier itself does not make the final judgment, but its output is used by a group of statistical classifiers. It gives a vector of six dimensions as its output, each of which corresponds to a confidence score for the corresponding category.

The current version of the rule-based classifier is very simple. It only checks whether a clue word in the dictionary appears in the legitimate neighborhood of the *medical problem*, and if it does, it adds $x_{category}$ in the following formula to the previous value of $x_{category}$ (each of the six $x_{category}$ is initially set to 0). In this formula, w is a window size fixed for each category and d is the distance between the occurrence of *medical problem* and the clue word.

$$x_{category} = \begin{cases} 1 & (w \leq d) \\ 0.8 & (d - w = 1) \\ 0.6 & (d - w = 2) \\ 0.4 & (d - w = 3) \\ \dfrac{1}{d - w} & (d - w \geq 4) \end{cases} \quad (1)$$

The window size is fixed to 4 for the present experiment. When $x_{category}$ for a category becomes greater or equal to 1, the $x_{category}$ is

Table 3 Definitions and examples of dictionaries

	Definition	Example
Keywords	Terms looked up in the sentence with a problem	One of his brothers has had *a myocardial infarction*.
Preceding words/phrases	Terms can be looked up before the problem in a sentence	Percocet, 5/325, 1-2 tabs PO q4-6h prn *pain*.
Succeeding words/phrases	The term looked up after the problem in a sentence	Return to the ER for high fevers, vomiting, *uncontrolled pains* or other concerns as needed.
Termination words	The term signifying the invalidation of signal words	In terms of his liver abnormalities, it was felt that *viral hepatitis* was in the differential but also was felt that Bactrim could be a cause of these abnormalities.
Self-indicative	The problem in a sentence that includes information itself, such as the prefix 'a-'	In '*asymptomatic*,' and '*non-tender*', the prefixes 'a-' and 'non-' are self-indicative
Personal nouns	Personal nouns qualifying nouns	His *pain*

Table 4 List of dictionaries for each category in assertion

Category	Keyword	Preceding	Succeeding	Termination	Self-indicative	Personal nouns
Present						x
Absent		x	x	x	x	
Possible		x	x	x		
Conditional	x					
Hypothetical		x	x			
Not_associated_with_the_patient	x					

x Indicates that the dictionary in each column exists for corresponding category.

set to 1 and the rest of the categories have 0 as their value. Furthermore, the classifier gives 1 to $x_{not\_associated\_with\_the\_patient}$ whenever *medical problem* appears in either the 'family history' section or the 'social history' section.

Extracting features for the statistical classifiers

In addition to the output of the rule-based classifier, our statistical classifiers use two sets of features: lexical context[12] (3-gram words) and syntactic context[12] (2-gram LGP syntax, verb, and section name) to complement the decision by the rule-based classifier.

Classifying assertions by statistical classifiers

Four statistical classifiers developed by MSR Asia[3] are used: SVM-binary, boosting, logistic-regression-binary, and SVM-multiclass. We chose them because: (1) SVM-binary has been shown to be effective in many learning scenarios, and is also feasible for a small training set or high-dimensional feature space[12]; (2) by combining many weak classifiers, boosting can achieve high performance in training data and relatively high performance in testing data[29]; (3) logistic-regression-binary is used extensively in the medical field, where it achieves high performance even when the features are correlated[34]; and (4) SVM-multiclass is used because of its ability to directly solve multi-label problems.[34]

Voting

The final results are decided by voting of the five classifiers, that is, the rule-based classifier and the four statistical classifiers. In a cross-validation procedure, we find that the SVM classifier performs better than the other three classifiers. Therefore, if the vote is a draw (2 vs 2), we choose the output of the SVM classifier as the final result.

Relation identifier

There are three distinct types of relations according to their argument classes: *problem-problem*, *problem-treatment*, and *problem-test*. We provide three modules for these three types. The first classifier classifies a relation into (PIP, Non-PIP). The second and the third modules classify a relation into (TrIP, TrAP, TrCP, TrWP, TrNAP, NonTrP) and (TeRP, TeCP, Non-TeP), respectively. Each of these three modules consists of the same set of four classifiers and its decision is based on the votes of the four classifiers. Classification is performed in the following four steps.

Normalizing sentences

Since concepts in a sentence are already recognized, each concept occurrence is replaced with a placeholder (eg, 'have dyspnea and tachypnea and required O2' is normalized to 'have [this.p] and [that.p] and required [this.tr]').

Extracting features for the relation classifier

The features used by the relation classifiers are divided into three sets: lexical context features, syntactic context features by the LGP, and a set of the features that we newly introduced for this task. The lexical context features and syntactic context features resemble those used by Sibanda, where they are described in detail.[12] The features that we newly introduced are described below.

Concepts co-occurrence (RF1)

In the medical domain, it is common for two concepts to co-occur in the same sentences as a matching pair with high frequency (eg, morphine and pain).[35] We select a set of pairs of concepts whose co-occurrence frequency exceeds a threshold. Then we examine if a pair in the set is a good indicator for classification of one of the relation classes (ie, PIP, TrIP, etc). If more than 80% cases in which the pair appears are classified as positive for a class, then the pair is considered as a positive pair for that class. We choose 291 concept pairs with high frequency that are positive for at least one of the relation classes. In the feature representation, these pairs are represented as 291 binary features.

Verb-based rules (RF2)

One of the major cues for relation identification are a set of verbs, such as 'improve,' 'worsen,' etc. These specific verbs tend to denote single or a few specific relations. After examining the training data, we chose 34 verbs as such relation-indicating verbs and use them as features.

N-gram-sequential patterns (RF3)

Some n-gram-sequential patterns (n=2, 3, 4, 5) were identified as useful features by examining the training data. For example, when classifying PIP/Non-PIP, we first extract the uni-gram pattern, bi-gram pattern, … and five-gram pattern. Some of them are indicative of PIP. For instance, 'associated with [this.p]' is a positive pattern. For each pattern P and a relation R, $Positive_{P/R}$ is the number of times that P appears in examples positive for R, and $Negative_{P/R}$ is the number of times P appears in

Table 5 Macro-averaged and micro-averaged results for the three tasks

	Macro-averaged			Micro-averaged		
	Precision	Recall	F measure	Precision	Recall	F measure
Concept	0.8653	0.8319	0.8482	0.8652	0.8334	0.8489
Assertion	0.8235	0.8071	0.8196	0.9392	0.9392	0.9392
Relation	0.6400	0.5547	0.5943	0.7400	0.7252	0.7326

examples negative for R. We only consider n-gram patterns that appear more than 60 times for a given relation. Then, we choose n-gram patterns, Ps, which satisfy either (2) or (3) as effective n-gram patterns for classification of R.

$$\frac{\text{Positive}_P}{\text{Positive}_P + \text{Negative}_P} \geq 0.7 \quad (2)$$

$$\frac{\text{Negative}_P}{\text{Positive}_P + \text{Negative}_P} = 1 \quad (3)$$

Assertion status (RF4)

The assertion status is also useful for relation identification and is used as a feature expressed by having one of six possible values set to 1 and the rest set to 0 in a six-dimensional binary feature vector.

Stanford dependency path (RF5)

Previous work[36 37] indicates syntactic features from multiple parsers improve relation extraction. Besides LGP, we used the Stanford dependency parser. The parser takes a sentence as input and outputs a dependency graph that demonstrates dependency relations between words in the sentence. For each pair of placeholder words (eg, [this.p], etc) to be classified, we identify a path in the dependency graph that connects them. We use all syntactic labels on the path as features. Features are represented as binary features, each of which corresponds to a syntactic label used in the Stanford parser.

Tense information (RF6)

Tense information is an important cue for certain relations. Suppose we have a *test*, and we conduct the *test* to examine if the patient has a *medical problem* (TeCP). Then it is likely that the sentence is in the future tense. In our implementation, we apply a simple rule to identify the tense of a sentence. We use SharpNLP to find the tense of a verb that appears in the right-most position in the sentence.

Word clustering (RF7)

Word clustering was applied to target words (ie, head nouns) and verbs to avoid the difficulties caused by data scarcity. Every target word and verb is given a class label, which denotes the cluster it belongs to.

Identifying relations by statistical classifiers

The same four statistical classifiers as used for assertion classification are employed. The second classification (TrIP, TrAP, TrCP, TrWP, TrNAP, Non-TrP) and the third classification (TeRP, TeCP, Non-TeP) are not binary. We first apply a set of binary classifiers, each of which is to determine whether a given relation belongs to the relation. When more than one classifier returns positive results, pairwise classifiers determine the winner. A pairwise classifier helps to classify the categories that are difficult to distinguish, for instance TrIP and TrCP, TrAP and TrNAP, etc.

Voting

The final results are determined by the voting of the four classifiers. As in the assertion task, we choose the SVM output when the vote was a draw.

RESULTS

Performance was measured by the three standard measures: precision (P), recall (R), and F measure (F). The results were micro-averaged and macro-averaged for each of the three tasks.

Table 6 Micro-averaged results from feature contributions for the concept task

Methods for the concept task	Precision	Recall	F measure	Increment
(b)+Baseline	0.8461	0.7866	0.8153	
(c)+CF1	0.8574	0.7982	0.8267	1.14%
(d)+CF2	0.8530	0.8091	0.8305	0.38%
(e)+CF3	0.8539	0.8170	0.8351	0.46%
(f)+CF4	0.8652	0.8334	0.8489	1.38%

CF1, pattern matching; CF2, word normalization; CF3, N-character-prefix-and-suffix; CF4, word clustering.

In the 2010 i2b2 challenge, the F measures of concept extraction, assertion classification, and relation identification of the top performing systems are 0.8523, 0.9362, and 0.7365, respectively.[38] Table 5 lists the results of our system for the three tasks. The results demonstrate that our system achieved state-of-the-art results. In particular, for small labeled training data, the rule-based method is shown to improve performance.

Concept task

Table 6 summarizes the improvement resulting from the addition of individual discriminating features. The baseline system used all the features except CF1, CF2, CF3, and CF4. We then listed the results by adding the features of CF1, CF2, CF3, and CF4. CF4 improved the F measure most.

Table 7 shows the performances of four different systems, that is, (1) Model_medication (OM), (2) Model_other (OO), (3) the combined model of Model_medication and Model_other, dynamically switched by elastic matching of the dosage-unit dictionary (CMOA), and (4) the combined model of Model_-medication and Model_other, dynamically switched by exact matching of the dosage dictionary (CMOS). The two combined models significantly outperform the two single models. The difference between CMOA and CMOS (0.3%) shows that the elastic matching works effectively. We used the z test on the F measure for testing the significance in (CMOA vs OM) and (CMOA vs OO). We divided 477 test records into 48 collections, each containing 9 or 10 records. As an F measure is calculated for each collection and model, respectively, we obtain 48 F scores for each of the models (ie, OM, OO, and CMOA). For the OM model, the SD of the 48 F scores is 0.019, and for the OO model, it is 0.017. The p value of the z test between the OM and CMOA models is 0.0397, and that between the OO and CMOA models is 0.0251. Since they both satisfy $\alpha \leq 0.05$, the CMOA model significantly outperforms the two single models (OM and OO).

To compare our system with the systems submitted to the 2010 i2b2 challenge, figure 3 summarizes the top 10 systems[39] and our system for concept extraction of *medical problem*, *treatment*, and *test* and the overall concept classes. Our system yields an F measure of 0.8524 for *medical problem*, 0.8441 for *treatment*, 0.8106 for *test*, and 0.8489 for all concepts (the sizes of the

Table 7 F measure results from every concept for the concept task

Methods	Problem	Treatment	Test	Micro-average
OM	0.8374	0.8490	0.8026	0.8421
OO	0.8580	0.8195	0.8404	0.8422
CMOA	0.8524	0.8441	0.8106	0.8489
CMOS	0.8500	0.8398	0.8102	0.8459

CMOA, combined Model_medication and Model_other with Adaptive dictionary; CMOS, combined Model_medication and Model_other with Standard dictionary; OM, only Model_medication; OO, only Model_other.

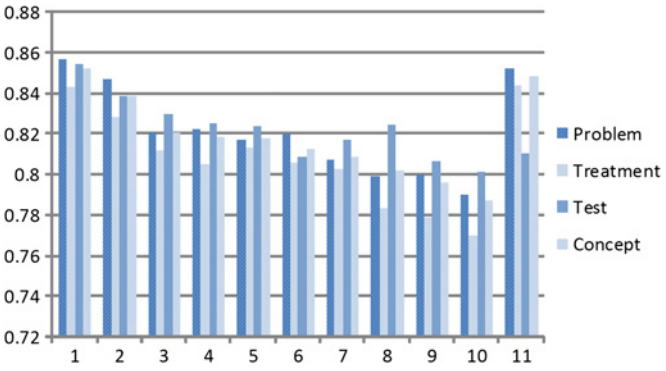


Figure 3 The results from the top 10 systems and our system for the concept task. On the abscissa, the numbers 1–10 denote the top 10 systems and the number 11 denotes our improved system.

training data for *medical problem*, *treatment*, and *test* are 11 968, 8500, and 7369, respectively). Our system significantly outperforms (by a margin of 3.35%) the top-performing system on *treatment*. This indicates that our approach of dynamic switching of the two different models, one for telegraphic sentences and one for ordinary sentences, works very well.

Assertion task

Table 8 gives the results for the assertion task by seven different methods: rule-based classifier (RC), SVM-binary with the rule-based features (SVMB_RF), boosting with the rule-based features (BOOST_RF), logistic-regression-binary with the rule-based features (LRB_RF), SVM-multiclass with the rule-based features (SVMM_RF), voting by the four statistical classifiers (SVM-binary, boosting, logistic-regression-binary, and SVM-multiclass) without the rule-based features (VC_WRF), and voting by combining all the classifiers (SVM-binary, boosting, logistic-regression-binary, SVM-multiclass, and rule-based classifier) with the rule-based features (VC_RF).

Table 8 shows that VC_RF is the best of the seven systems. RC outperforms VC_WRF by a margin of 1.88%. This illustrates the effectiveness of the rule-based classifier and the features produced by it. The statistical classifiers do not perform well without the rule-based features, as clearly shown when there is serious scarcity of data. For the small categories such as *conditional* and *possible*, the rule-based system outperforms the statistical classifiers by margins of 16.71% and 23.63%, respectively.

Relation task

Table 9 summarizes the performance improvement by the seven types of discriminating features. RF3 showed the most improvement. Together with the contributions of RF1 and RF2, this shows the importance of feature engineering in this task. The contribution of RF7, which is significant, shows that clustering of words alleviates the problem of data scarcity. Our system compared favorably with the state-of-the-art systems[40] in the 2010 i2b2 challenge that did not rely on external web-based knowledge sources.

Table 9 Micro-averaged results from feature contributions for the relation task

Methods for the relation task	Precision	Recall	F measure	Increment
(b)+Baseline	0.6984	0.6411	0.6685	
(c)+RF1	0.7029	0.6567	0.6790	1.05%
(d)+RF2	0.7079	0.6603	0.6833	0.43%
(e)+RF3	0.7012	0.6935	0.6973	1.40%
(f)+RF4	0.7106	0.7015	0.7060	0.87%
(g)+Pairwise classifiers	0.7226	0.7144	0.7185	1.25%
(h)+RF5	0.7249	0.7173	0.7212	0.27%
(i)+RF6	0.7403	0.7104	0.7251	0.39%
(j)+RF7	0.7400	0.7252	0.7326	0.75%

RF1, concepts co-occurrence; RF2, verb-based rules; RF3, n-gram-sequential patterns; RF4, assertion knowledge; RF5, Stanford dependency path; RF6, tense information; RF7, word clustering.

DISCUSSION

Our rule-based assertion system has the following advantages compared with the state-of-the-art methods. The dictionary we manually constructed is large and comprehensive, so that we can fully exploit external knowledge. We also use a voting mechanism for integrating the results of the different classifiers. Moreover, syntactic features are used in our classifiers. While syntactic features in previous works have not been used as widely as lexical features, the experiment results show that they improve the assertion task. This is one of the reasons why our system outperforms the other state-of-the-art systems.

Accurate marking of NPs and APs impacts on overall performance. Since only 88% of phrases are correctly marked for the training data even by the modified version of SharpNLP, 12% of concepts failed to be passed to the extraction stage. This shows that NLP tools need to be further improved to cope with the peculiarities of medical language. Medical records have many telegraphic sentences that may be deemed ungrammatical according to ordinary English grammar. Even non-telegraphic sentences contain many acronyms, local constructions that are not covered by ordinary English grammar, etc. These are challenges for NLP tools developed for the general domain.

CONCLUSION

This paper describes a state-of-the-art information extraction system based on extensive feature engineering combined with rule-based and machine learning methods. In order to treat

Table 8 Micro-averaged F measures for the assertion task from various methods

Assertion category	Training set size	RC	SVMB_RF	BOOST_RF	LRB_RF	SVMM_RF	VC_WRF	VC_RF
Present	13 025	0.9497	0.9510	0.9491	0.9513	0.9579	0.9386	0.9608
Absent	3609	0.9290	0.9322	0.9305	0.9315	0.9372	0.8858	0.9418
Possible	883	0.6800	0.7010	0.6291	0.6599	0.7001	0.4437	0.7019
Conditional	171	0.3371	0.3913	0.3372	0.3492	0.3472	0.17	0.3938
Hypothetical	717	0.7809	0.7870	0.7897	0.7988	0.9465	0.8122	0.9443
Not_associated_with_the_patient	145	0.8794	0.8786	0.8889	0.7607	0.9790	0.8075	0.9720
Overall	18 550	0.9220	0.9239	0.9214	0.9239	0.9374	0.9032	0.9392

BOOST_RF, boosting with the rule-based features; LRB_RF, logistic-regression-binary with the rule-based features; RC, rule-based classifier; SVMB_RF, SVM-binary with the rule-based features; SVMM_RF, SVM-multiclass with the rule-based features; VC_WRF, voting by the four statistical classifiers (SVM-binary, boosting, logistic-regression-binary, and SVM-multiclass) without rule-based features; VC_RF, voting by combining all classifiers (SVM-binary, boosting, logistic-regression-binary, SVM-multiclass, and rule-based classifier) with the rule-based features.

telegraphic sentences interspersed among ordinary sentences, we proposed a method of dynamic switching of models. The method significantly improved the concept extractors. Since telegraphic sentences are interspersed among ordinary sentences in medical records, the same idea can be generalized and applied to other tasks that deal with medical records. In assertion classification, the result of a rule-based classifier is used as a feature in statistical classifiers, which successfully combine the rule-based approach with an ML-based classifier. This works well for small classes for which the training data are limited. In relation identification, the architecture of the pair-wise classifiers improves the performance significantly. A set of new discriminating features introduced in this paper are also shown to be very effective.

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