Automated Activity Recognition in Clinical Documents

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Abstract

We describe a first experiment on the identification and extraction of computer-interpretable guideline (CIG) components (activities, actors and consumed artifacts) from clinical documents, based on clinical entity recognition techniques. We rely on MetaMap and the UMLS Metathesaurus to provide lexical information, and study the impact of clinical document syntax and semantics on activity recognition.

Keywords. Clinical entity recognition, computer interpretable guideline, UMLS Metathesaurus.

Introduction. Clinical practice guidelines are systematically developed documents specifying the activities, resources and personnel required to cure or treat an specific illness or medical condition (Field and Lohr (1990)). The need to instantiate them into clinical protocols and workflows has given rise to computer-interpretable guidelines (CIGs) (De Clercq et al. (2008)), i.e., formal representations of the care process or plan, and to several natural language processing (NLP) techniques aimed at automating the costly manual CIG generation process (Kaiser et al. (2007), Serban et al. (2007)). All NLP approaches leverage on annotated biomedical resources (e.g., the CLEF corpus from Roberts et al. (2007) and Mykowiecka and Marciniak (2011)), or on frameworks such as cTAKES (Savova et al. (2010)). The key lexical-semantic resource in this domain is the US National Library of Medicine’s Unified Medical Language System (UMLS) Metathesaurus (Bodenreider (2004)), complemented by its front-end MetaMap (Aronson and Lang (2010)).

In this paper we conduct a first experiment on how to apply entity recognition techniques inspired by Abacha and Zweigenbaum (2011), to recognize CIG components in medical documents. The process dimension of CIGs consists of four pillars: (1) activities to be executed; (2) the resources they use or consume; (3) the actors that execute them; (4) control flows and gates that temporally constrain activities. We focus in this paper on activities, the main building block of CIGs, and to a lesser extent on resources and actors. All these components are denoted by content words and can be used to build CIG fragments. We rely on MetaMap annotations and evaluate our techniques over an UMLS-annotated clinical corpus.

CIGs and Activities. Activities are entities difficult to identify with current resources: within clinical documents, in fact, not only verbs (VBs) but also proper nouns (PNs), common nouns (NNs) and, more in general, noun phrases (NPs)\(^1\) can refer to them. Figure 1 shows an example from the type-2 diabetes guideline of the National Institute for Health and Clinical Excellence (NICE) (NICE - NHS (2009)) expressing a conditional CIG/process fragment, annotated automatically with MetaMap. To correctly extract the “deep” intended representations it is necessary to recognize that the two entities “blood glucose control” and “oral glucose-lowering medication” are activity tokens. MetaMap annotations provide a clue, but we still need to “filter out” the “clinical attribute” UMLS annotation. We want to understand how this information can be used for this task within an entity recognition framework.

Clinical Entity Recognition. Let \(\vec{c}\) denote a vector of clinical entity type labels, and \(\vec{\alpha}\) a vector of input noun phrases (NPs) or entities. The goal of clinical entity recognition, see Abacha and Zweigenbaum (2011), can be formulated as the task of finding the best scoring vector of clinical

\(^1\)In this paper we refer to the Penn Treebank part-of-speech (POS) notation as described by Marcus et al. (1993).
entity type labels: \( \hat{c}^* = \arg \max \{ \hat{c} | \mu(\rho(\hat{\alpha}, \hat{c})) \} \), where \( \mu(\cdot) \) denotes a recognizer built using a classification model (e.g., a logistic regression algorithm), and \( \rho(\cdot, \cdot) \) is a feature extraction function. In the following paragraphs we study this task w.r.t. the set \{activity, resource, actor, other\} of entity types.

The SemRep corpus. Since no UMLS annotated clinical guideline corpora are available for research purposes, we ran our experiments over the SemRep corpus by Kilicoglu et al. (2011), a small annotated clinical corpus whose domain largely overlaps with that of guidelines. It consists of 500 clinical excerpts (MedLine/PubMed) and contains 13,948 word tokens manually annotated by clinicians and domain experts, covering the whole clinical domain. UMLS concept types annotate a total of 827 NPs.

Features. The focus of our experiments is to understand the predictive power of syntax and semantics for CIG entity recognition, and in particular for activity recognition. Intuitively, both syntax and semantics can contribute to the prediction of clinical entity types, but it is not a priori clear which one contributes more. Similarly to Zhou and He (2011) we used the Stanford parser (see Klein and Manning (2003)) to extract syntactic features, and MetaMap to extract semantic features. We harvested clinical types by mapping UMLS concept types returned by MetaMap to their subsuming clinical types. In the top of Table 1 we show a sample of UMLS concept types subsumed by “activity”, “resource”, “actor” and “other”, whereas in its bottom we summarize the extracted features, described in detail below.

By mining the NPs sentence parse trees, we extracted the following syntactic features: depth of nesting (nest); position in the phrase (pos); occurrence in a subordinated phrase (sub). The intuition behind these features is that certain types may correlate strongly with syntax (e.g., one would expect “resource” to annotate an object NP).

The semantic features were extracted by computing several measures of label overlap and frequency. The rationale of these features is that, while MetaMap outputs many possible clinical meanings of the constituent NNs of an NP entity, giving rise to multiple “activity”, “resource”, “actor” and “other” annotations per NN and NP, it tends to output meanings that are semantically related (within the UMLS Metathesaurus hierarchy) to the NP’s intended type.

We measured the raw frequency freq of the NP entity type \( c \) in the SemRep corpus, the degree of annotation overlap \( \text{hd} \) between the bag of possi-
Table 1: Top: CIG entity labels and sample UMLS concept types they subsume. Bottom: NP features considered; the class label is the dependent feature we want to predict.

| feature | description | value f |
|---------|-------------|---------|
| nest    | nesting level in tree | integer ∈ ℤ |
| pos sub | position w.r.t. verb | subject, predicate |
| freq    | freq. of label in corpus | integer ∈ ℤ |
| rel freq. of label in NP | real ∈ [0, 1] |
| head/NP overlap | real ∈ [0, 1] |
| label/NP overlap | real ∈ [0, 1] |
| class   | NP entity type | act., actor, res., other |

In our experiments the main goal was to evaluate activity recognition features rather than classifier design and evaluation. We thus relied on standard classification models from the known Weka\(^2\) data mining framework. We trained and evaluated the following classifiers: (i) logistic classifier (Logit), (ii) support vector machine (SVM), (iii) naive Bayes classifier (Bayes), (iv) neural network (Neural), and (v) decision tree (Tree). To measure the significance of each single feature, we removed each time a feature \(F_i\) from the space \(\{F_1, \ldots, F_7\}\) of syntactic and semantic independent features from Table 1 and retrained and reevaluated the classifiers w.r.t. the feature space \(\{F_1, \ldots, F_i-1, F_i+1, \ldots, F_7\}\).

In parallel to this, we studied the impact of context over activity recognition, and its interplay with our features. To this end we considered a baseline scenario, in which context is restricted to NPs, and a scenario in which we take into consideration all the annotated NPs of a SemRep sentence. This distinction is important since SemRep is a small and sparsely annotated corpus, for which enhanced feature spaces may not prove informative. These two scenarios were modeled as follows. (1) A set of NP observations: for each NP \(\alpha\) in SemRep, we extracted the feature vector \((f_{i1}^\alpha, \ldots, f_{i7}^\alpha, c_\alpha)^T\). (2) A set of sentence observations: for each vector \((\alpha_1, \ldots, \alpha_k)^T\) of annotated NPs in a SemRep sentence, we extracted feature vectors \((f_{i1}^{\alpha_1}, \ldots, f_{i7}^{\alpha_1}, c_{\alpha_1}, \ldots, f_{i1}^{\alpha_k}, \ldots, f_{i7}^{\alpha_k}, c_{\alpha_k})^T\).

For each combination of classifier feature and scenario, we performed a 10-fold cross-validation to measure precision (Pr), recall (Re), F1-measure, and the overall accuracy (Ac) of the classifiers for the activity recognition task\(^3\).

Results and Discussion. The baseline scenario (see Figure 2, left) shows a drop in average precision, recall, F-measure and accuracy when \(hd\) and \(freq\) are disregarded, and a minor drop when \(ls\) is disregarded. The removal of syntactic features on the other hand has a smaller effect. Considering sentence context (see Figure 2, center), we can observe a greater impact for \(sub\), and a minor drop when \(ls\) is disregarded. But sentence context gives rise also to a clear decrease in average classifier performance. Thus \(sub\), while significant, is less useful than the semantic features.

This last observation is substantiated by corpus evidence. One way to see how, is to focus on the distribution of syntax relatively to corpus domain. Syntactic features can be approximated by function words\(^4\) (e.g., subordinators (INs) such as “if”

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\(^2\)www.cs.waikato.ac.nz/~ml/weka/

\(^3\)For reasons of space, we present here a summary of the results obtained; for a more detailed description, please refer to www.inf.unibz.it/~cathorne/vericlig/ijcnlp2013-exp.pdf

\(^4\)For the POS tagging we relied on a Natural Language Toolkit (NLTK) 3-gram tagger by Bird et al. (2009), trained over the (POS annotated) Brown corpus.
or “then”, coordinators (CCs) such as “or”).

We compared to SemRep: (i) a subset of the Brown corpus (Francis and Kucera (1964)), (ii) a corpus of business process specifications (Friederich et al. (2011)), (iii) a subset of the NICE diabetes-2 guideline (NICE - NHS (2009)), (iv) a subset of the NICE eating disorders guideline (NICE - NHS (2004)), and (v) a subset of the NICE schizophrenia guideline (NICE - NHS (2010)). We run the following statistical tests (see Gries (2010)) at \(p = 0.01\) significance: (1) a \(t\)-test (null hypothesis: cross-corpora function word mean relative frequency is 0.20); (2) a \(\chi^2\)-test of independence (null hypothesis: function word distribution is correlated to corpus domain). The test results (see Table 2) show that syntax is uniform across domains, and thus has a more limited impact relatively to semantics.

Syntax, however, can be leveraged to optimize prediction results when exploited by classifiers sensitive to categorical data. The classifier that performed better overall was the decision tree (see Figure 2, right), which seems to exploit better the more limited impact of \(\text{sub}, \text{pos}, \text{and nest}\).

Conclusions and Further Work. We have conducted preliminary experiments on automatic clinical activity recognition using MetaMap and entity recognition techniques. We experimented our techniques on the SemRep gold standard UMLS-annotated corpus. Our experiments suggest that the semantic environment of an entity is more useful for this task. Corpus analysis on SemRep and other corpora seems to confirm this observation. In the future, we plan to consider more powerful classification models for NLP, such as conditional random fields (CRFs), able to exploit possible dependencies among features. We plan to focus on document semantics, by considering more complex semantic features (based on, e.g., thesaurus-based similarity metrics). Finally, to better cope with data sparseness we intend to consider a bigger corpus by integrating SemRep with, e.g., the i2b2 clinical corpus as suggested by Abacha and Zweigenbaum (2011).

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\(\chi^2\) and \(t\)-tests of independence across corpora and domains.

| corpus       | size (words) | domain         | rel. freq. |
|--------------|--------------|----------------|------------|
| Brown        | 1,391,708    | news           | 0.16       |
| Friederich   | 3,824        | processes      | 0.17       |
| SemRep       | 13,948       | clinical       | 0.18       |
| diabetes2    | 7,109        | clinical       | 0.16       |
| eating dis.  | 5,078        | clinical       | 0.17       |
| schizophrenia| 5,367        | clinical       | 0.18       |

| \(\chi^2\) | \(p\)  | df. | \(t\)-score | \(p\)  | df. |
|-------------|--------|-----|-------------|--------|-----|
| 43.13       | 0.00   | 2   | 1.03        | 0.36   | 5   |

Table 2: **Top:** Function word relative frequency across corpora and domains. **Bottom:** Statistical tests (\(\chi^2\)-test of independence and \(t\)-test).

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\(^5\)www.unibz.it/~cathorne/vericlig
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