Distant-Supervised Named Entity Recognition with Trigger

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Abstract

We propose distant-supervised model for Named Entity Recognition (NER) that only requires a few annotated corpora and corresponding trigger templates, which may trigger a certain Named Entity class in the corpora. With trigger template matching on large number of unannotated corpora, it permits the iterative and incremental design of named entity recognition.

1 Introduction

Although modern high-performance NER systems require a large amount of annotated corpora, annotated corpora for domain specific NER are usually of limited size because building NE corpora is costly and time-consuming. In this paper, we propose distant-supervised model for NER that only requires a few annotated corpora and corresponding trigger templates. Trigger templates are representing human natural-language explanation that may trigger a certain Named Entity in the corpora. Examples of trigger are shown in Fig. 1.

Sentence	Trigger
The clinical utility of <Chemical> FK 506 </Chemical> is complicated by substantial hypertension and nephrotoxicity .	The clinical utility of
Inappropriate use of <Chemical> carbamazepine </Chemical> and vigabatrin in typical absence seizures .	Inappropriate use of

Figure 1: Examples of trigger

2 Approach

2.1 Soft Trigger template matching

Given a word sequence $x = (x_1, x_2, ..., x_N) \in X_{label}$, encode it into contextualized word representation $h = (h_1, h_2, ..., h_N)$ with BERT. Assume that words of triggers corresponding to entity $x_{ent} = (x_{entword}, x_{enttype})$ in the sentence are (x_2, x_3, x_8), we encode corresponding words (x_2, x_3, x_8) into template vector $TempVec$. Then, we map the template vector $TempVec$ to corresponding entity type $x_{enttype}$.

Using extracted $TempVec$ and BERT results of word sequence in unlabeled corpora, we learn template matching network. Template matching network jointly learns template-level matching classification and token-level sequence tagging for deciding slot positions as shown in Fig. 2.

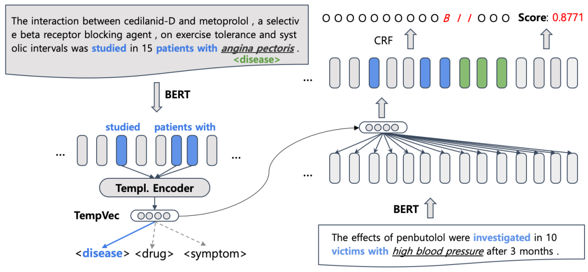

Figure 2: Template matching network

2.2 Bootstrapping

A sentence can be matched with more than one template. Using both template-level matching score and token-level slot score, we find the best match template. Using the token-level slot result of the best match template as an annotation for a sentence, we augment the dataset. However, there should be many missing entity mentions in such noisy annotation. Thus, we are planning to build higher level CRFs with positive unlabeled learning.

3 Related works

3.1 Weakly supervised NER

Current existing works on weakly supervised NER mostly use domain-specific dictionary, weakly labeled data and unannotated target domain corpus.

Weakly Labeled data (Ni et al., 2017) created automatically labeled NER data for a target language via annotation projection on comparable corpora. Then, filter out WL (Weakly Labeled) sentences by statistical method.

- **cons** : Regarding unlabeled words as O so that it cannot deal with incomplete annotation.

Dictionary + Partial CRF (Shang et al., 2018) and (Yang et al., 2018) proposed weakly supervised methods by using domain-specific dictionary and unannotated target domain corpus. They both employ Partial CRFs which assign unlabeled words with all possible labels and maximize the total probability.

- **pros** : Handle the problem of incomplete and noisy annotation
- **cons** : Relies on domain-specific seed dictionary

Weakly Labeled Data + Partial CRF (Cao et al., 2019) automatically constructs WL data from Wikipedia anchors and split them into high-quality and noisy data. Then, train classification module, which regards name tagging as a multi-label classification problem, with noisy data first and fine-tune with high-quality data. After pre-train this classification module, share the overall NN with the sequence labeling module. Then, use sequence labeling module to infer the named entity.

- **pros** : No relies on domain-specific seed dictionary
- **cons** : Relies on exact string matching with Wikipedia. weakly labeling doesn't consider the context of sentence. (Also, no code for the project)

Weakly Labeled Data + Neural Correction (Zhu et al., 2019) constructs WL data from Wikipedia and DBpedia. When it applies exact string matching on Wikipedia and DBpedia, it uses the title and anchored strings of hyperlinks assuming that they are most likely to be named entities. With WL data and corresponding human annotated data (DocRED), it implements semi-supervised correction model with curriculum learning to correct the false-negative entity labels.

- **pros** : Shows effectiveness of curriculum learning using WL data. (train the most easiest one first, which has high-confidence WL data. Then train more difficult one, which has low-confidence.)
- **cons** : It can only be applied to general NER tasks such as CONLL and ONTONOTES. It cannot be applied to domain-specific tasks.

Incomplete Annotation (Jie1 et al., 2019) proposed an approach to tackle the incomplete annotation problem. It introduces q distribution to model missing labels. It makes each possible label sequence can get a certain probability scores so that missing labels can be well-modelled instead of traditionally uniform distribution for all possible complete label sequence

- **pros** : Proposed method shows effective solution for incomplete annotation. It can be applied to our WL data generated by template matching network.

3.2 Unsupervised NER

Prior computed from Knowledge Base (Liu et al., 2019) proposed unsupervised NER method that just using a prior type information p, pre-computed from entity popularity information available in many KB.

- **pros** : Incorporating with type priors shows effectiveness.

Only using word embedding (Luo et al., 2019) proposed fully unsupervised NER method only using word embedding. Separate entity span detection and entity type prediction. First use Gaussian-HMM to learn the latent Markov process among NE labels with the IOB tagging scheme and then feed the candidate entity mentions to a Deep Autoencoding Gaussian Mixture Model for their entity types.

- **pros** : First fully unsupervised NER without any external knowledge. Gaussian-HMM can be applied to our project to detect entity span.

4 Our novelty

Current existing weakly supervised NER methods are mostly rely on exact matching between input and dictionary or knowledge base. In this project, we will implement soft rule matching between input and human natural-language explanation. Thus, it may resolve the issues of exact matching and show effectiveness of human explanation on prediction.

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