ANEAS Distant Supervision for Low-Resource Named Entity Recognition

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Abstract

Distant supervision allows obtaining labeled training corpora for low-resource settings where only limited hand-annotated data exists. However, to be used effectively, the distant supervision must be easy to obtain. In this work, we present ANEA, a tool to automatically annotate named entities in text based on entity lists. It spans the whole pipeline from obtaining the lists to analyzing the errors of the distant supervision. A tuning step allows the user to improve the automatic annotation with their linguistic insights without having to manually label or check all tokens. In six low-resource scenarios, we show that the F1-score can be increased by on average 18 points through distantly supervised data obtained by ANEA.

1 Introduction

Named Entity Recognition (NER) is a core NLP task necessary for a variety of applications from information retrieval to virtual assistants. While there exist some large, hand-annotated corpora like (Tjong Kim Sang and De Meulder, 2003) or (Wieschedel et al., 2011), these are limited to a selected set of languages and domains. For many low-resource languages and domains, it is not possible to manually label every token of large corpora due to time and resource constraints. To overcome this problem, weak or distant supervision methods have become popular which can automatically annotate unlabeled, raw text (Mintz et al., 2009). Even in low-resource settings, unlabeled text is often available and research has shown that it can be a useful training resource in the absence of expensive, high-quality labels.

For NER, a very common approach is to use lists, dictionaries or gazetteer of named entities (e.g. a list of person names or cities) and assign each word in the corpus the corresponding named entity label if it appears in this list of entities. This is done e.g. in (Ratinov and Roth, 2009; Gerner et al., 2010; Yang et al., 2018; Lange et al., 2019; Peng et al., 2019). However, this idea has several difficulties such as obtaining these dictionaries (e.g. a list of city names in Estonian) or adapting the matching procedure to the specific language and domain (e.g. deciding for or against lemmatization trading off recall and precision). In practice, distant supervision can only be beneficial and save resources if it is easy and fast to deploy.

The ANEA tool we present provides the functionality to actually use this distant supervision approach in practice for many languages and named entity types while minimizing the amount of manual effort and labeling cost. A process is provided to automatically extract entity names from Wikidata, a free and open knowledge base. The information is used to automatically annotate named entities for large amounts of unlabeled text. The tool also supports the user in tuning the automatic annotation process. This enables language experts to efficiently include their knowledge without having to manually annotate many tokens. Both a library and a graphical user interface are provided to assist users of varying technical backgrounds and different use-cases. In an experimental study on six different scenarios, we show that ANEA outperforms two baselines in nearly all cases regarding the quality of the automatic annotation. When used to provide distantly supervised training data for a neural network model, it creates on average a boost of 18 F1 points with less than 30 minutes of manual interaction.
2 Related Work

A variety of open-source tools exist to manually annotate text. While their focus is on the manual annotation of data, some of them support the user with certain degrees of automation. A token can be labeled automatically if it has been labeled before by the user in WebAnno (Yimam et al., 2014) and TALEN (Mayhew and Roth, 2018). In TALEN, a bilingual lexicon can be integrated but just to support annotators that do not speak the language of the text. WebAnno and brat (Stenetorp et al., 2012) allow importing the annotations of external tools as suggestions for the user. The focus is, however, still on the user manually checking all tokens. Also, the annotator is not able to use their insight to directly influence and improve the external tool like in the tuning process of ANEA.

In the area of information extraction, the tools by Gupta and Manning (2014), Li et al. (2015) and Dalvi et al. (2016) allow the user to create rules or patterns, e.g. “[Material] conducts [Energy]”. They can, however, require a large amount of manual rule creation effort to obtain good coverage for NER. With Snorkel (Ratner et al., 2019), a user can define similar and more general labeling functions. Oiwa et al. (2017) presented a tool to manually create entity lists. These lists could be imported into ANEA.

NER is closely related to entity linking. Zhang et al. (2018) presented a system to automatically link entities in many languages but focus on disaster monitoring.

3 Workflow

The workflow is visualized in Figure [1a] and we provide an online video that shows an exemplary walkthrough. The process is split into four parts:

- **Extraction**: The user starts with searching for the category names of the entity types that should be extracted (e.g. person or film). The tool will then automatically extract the names of all the corresponding entities (e.g. for person: “Alan Turing”, “Edward Sapir”, ...). As the source for the extractions, we use a dump of Wikidata. It is a free and open knowledge base that is created both by manual edits and automatic processes. At the time of writing, it contains over 85 million items. For most items, the names are available in multiple languages (e.g. for city names 8k in English and 2.5k in Estonian). Additionally, the user can also provide existing lists of entity names in case of a very specific domain.

- **Automatic Annotation**: The automatic annotation is performed by checking each word against the list of extracted entities. A word (or token) is assigned the label of the entity name it matches. If matches of several entity names overlap, the longest match is used. I.e. for the string “United Arab Emirates” the entity name of the country is preferred over the substring “United” (the airline) if both are in lists of entities.

- **Evaluation**: If a small set of labeled data exists, it can be used to evaluate the automatic annotation. The tool can calculate precision, recall and F1-score directly. It also reports the tokens that were most often labeled incorrectly or not labeled. For a more in-depth analysis, for each token one can check which label was assigned, which alternative labels could have been assigned and to which entities they correspond. This allows a user to easily understand issues of the automatic annotation.

- **Tuning**: ANEA provides a list of options with which the automatic annotation can be improved. Guided by the evaluation from the previous step, this allows the user to easily insert expertise about the language into the annotation process and prevent common mistakes while still avoiding to annotate or post-edit many tokens manually. The options include filtering common false positives, stopword removal, adding alias names (like ”COLING” for the ”International Conference on Computational Linguistics”), splitting entity names, removing diacritics, requiring a minimum character length for the entities or fuzzy matching of entities. The effects of such a tuning process are visualized in Figure [1e] for an Estonian dataset and the location label. Adding lemmatization in tuning-step 1 increases recall due to the rich morphological structure of the language that can hinder the matching. In step 3, location entities are given a higher priority if they conflict with person entities on the same token. In the last tuning-step, another gain can be obtained by extracting additional entity lists for Estonian locations based on the evaluation feedback. After the (optional) tuning process, unlabeled text can be automatically annotated.
Figure 1: Overall workflow of ANEA (a) and development of precision and recall during the tuning process on the Estonian data (b). On the x-axis, the setting changes over time are reported.

4 Experimental Evaluation

4.1 Datasets

We selected a variety of datasets that reflect different languages and entity granularities. The first 1500 tokens of each dataset are used as labeled training instances. Garrette and Baldridge (2013) reported that this is a number of tokens that can be annotated within two hours for a low-resource POS task. We think that this is a reasonable amount of labeled data that one can expect even in a low-resource setting and it is also necessary for training the baselines we compare to. For English (En), the CoNLL03 dataset is probably the most popular NER dataset. It was created for the CoNLL-2003 shared task (Tjong Kim Sang and De Meulder, 2003). To obtain a dataset with a high-resource language, but a more specialized domain, we manually annotated the location labels from the CoNLL03 dataset with more specific labels. To evaluate a non-English scenario with a fine-grained and less common label, we manually annotated Spanish (Es) news articles with the label movie. For evaluating the low-resource language scenario, datasets in Estonian (Et) (Tkachenko et al., 2013), West Frisian (Fy) (Pan et al., 2017) and Yoruba (Yo) (Alabi et al., 2020) were chosen. The manually labeled data we created for this evaluation is made publicly available.

4.2 Machine Learning Models

We evaluate against two baselines that should, like ANEA, be easy and quick to use and do not require extensive development of hand-engineered features. The Stanford NER tagger is a popular tool based on Conditional-Random-Fields (CRF) which we use in their suggested configuration. For the second baseline - a deep-learning model - we did a preliminary study on held-out CoNLL03 data to find good settings for a low-resource scenario. This Neural Network (NN) performed better in the low-resource setting than more complex ones with a larger context or a Bi-LSTM+CRF architecture like in (Lample et al., 2016). To easily apply the model to many different languages, we used pretrained fastText embeddings (Grave et al., 2018) which are available in 157 languages. Model details are given in our published code. In the high-resource setting on the full CoNLL03 dataset (>250k labeled tokens), both baselines achieve an F1-score of 87.

4.3 Experimental Setup

Experiment A: Here, the quality of the automatic annotation is evaluated. The CRF is trained on the 1500 labeled training tokens of each dataset. Similarly for the Bi-GRU, the first 1000 tokens are used for the training and the remaining 500 tokens are held-out as the development set to select the best performing epoch and avoid overfitting. For ANEA, we report the scores with and without the tuning phase. ANEA No Tuning just uses the default settings without any labeled supervision and no manual
Table 1: Results of Experiment A (a) and Experiment B (b) on the test data. We report precision/recall/F1-score in percentage (higher is better).

Experiment B: For evaluating the effect of the distant supervision, unlabeled tokens are automatically annotated by the CRF, the NN and ANEA with Tuning. The NN model is then retrained on both the manually labeled and the distantly-supervised instances. 200k tokens from each of the datasets are used as unlabeled data. For Spanish, West Frisian and Yoruba, ca. 15k and 70k and 18k tokens are used respectively due to the smaller dataset sizes. These texts are disjoint of the labeled training and test data.

4.3.1 Results

The results of Experiment A are given in Table 1a. The CRF approach can provide a high precision but often has a very low recall due to the limited amount of training data. The NN can leverage the pre-training of the embeddings on large amounts of unlabeled text. However, the training data seems not enough to reach a competitive performance. Our tool struggles most with organizations as these are stored as several different entity types in Wikidata. Another issue is the existence of false positives of words that have other meanings beyond entity names, e.g. the Turkish city “Of”. Nevertheless, reasonable results are obtained even if the amount of labeled tokens is too low for the baselines to learn anything meaningful (cf. En CONTINENT or Et ORG). Even without any labeled data, we are often able to reach competitive performance. Using the tuning process is helpful to boost the performance further. The possibility for the user to trade-off precision and recall can be seen in several cases (e.g. En LOC or Et PER). Overall, ANEA outperforms the other baselines in all metrics in a majority of the settings. It achieves the best F1-score in all but one case.

The higher quality of the automatic annotation is also reflected in Experiment B (Table 1b). For 14 out of 16 evaluated entity types, the distant supervision provided by ANEA achieves the largest improvements. On average, it increases the classifier’s performance by 18 points F1-score.

5 Conclusion

We presented a tool to obtain large amounts of distantly supervised training data for NER in a quick way and with few manual efforts and costs. While the annotation itself is automatic, the user is able to tune it to add their expertise. To support users of varying technical backgrounds, both a library and a graphical user interface are provided. The experiments showed its usefulness in six different language and domain settings. The tool, further information and technical documentation and the additional model code and evaluation data are available under the Apache 2 license online.

https://github.com/uds-lsv/anea
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