TRAINING NER MODELS: KNOWLEDGE GRAPHS IN THE LOOP

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What is NER?

Named Entity Recognition (NER) is a sub-task of information extraction with the objective to identify and classify named entities mentioned in unstructured text. It is commonly approached as a supervised classification problem. This means that annotated training materials are required.

Common NE types are available

Pre-annotated corpora covering common cases such as Person, Organization, Location etc. are easy to obtain.

What about my case?

The recognition of more exotic types presents a bootstrapping problem. How can we train a classifier without the time and resource costs associated with manually annotating and curating a sizeable training dataset?

Our approach

We aim at producing annotated training data semi-automatically, distantly supervised using a Knowledge Graph. As the pre-requisite we require an initial vocabulary for a domain and raw text of the same domain of interest.

Workflow

1. Taxonomy and Ontology build
   Knowledge Graph
2. PoolParty Extractor accesses knowledge graph
3. PoolParty Extractor annotates the corpora
4. Use annotated corpora to train a new ML NER model
5. PoolParty Extractor uses the new model

Evaluation method

To set a baseline for our evaluation we used the CoNLL-2003 shared task corpus and the NCBI-disease corpus.

- Use the human annotated training corpus to train models.
- Use the evaluation corpus for each dataset to evaluate the models in terms of Precision (PR), Recall (RE) and F1 score.
- For each of the NE types, create a taxonomy based on the labels of the NE found on the training corpus.
- Re-annotate the raw training corpora using the PoolParty Extractor API, configured to use the corresponding Concept Scheme.
- Finally, use the re-annotated corpora to train NER models and evaluate the new models using the corresponding human annotated evaluation corpus.

Results

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Vocabulary</th>
<th>Entity Type</th>
<th>Annotation Method</th>
<th>Human</th>
<th>Automatically</th>
<th>( \Delta P@1 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>CoNLL-2003</td>
<td>Extracted</td>
<td>Person</td>
<td></td>
<td>51.2</td>
<td>70.1</td>
<td>18.9</td>
</tr>
<tr>
<td>CoNLL-2003</td>
<td>Extracted</td>
<td>Location</td>
<td></td>
<td>54.2</td>
<td>71.3</td>
<td>17.1</td>
</tr>
<tr>
<td>CoNLL-2003</td>
<td>Extracted</td>
<td>Organization</td>
<td></td>
<td>51.2</td>
<td>70.1</td>
<td>18.9</td>
</tr>
<tr>
<td>NCBI-disease</td>
<td>Extracted</td>
<td>Disease</td>
<td></td>
<td>52.2</td>
<td>71.4</td>
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</tr>
<tr>
<td>NCBI-disease</td>
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</tr>
</tbody>
</table>

Evaluation results of OpenNLP NER on human annotated test corpora. Annotation method refers to the training corpora in each case. \( \Delta P@1 \) is the difference in F1 scores between automatic and human annotations. Vocabulary identifies how the controlled vocabulary for automatic annotations was created: either already provided human annotations were collected and used for automatic re-annotation or Disease branch of MeSH-2019.

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