TRAINING NER MODELS: KNOWLEDGE GRAPHS IN THE LOOP

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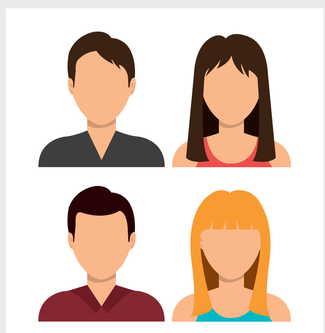
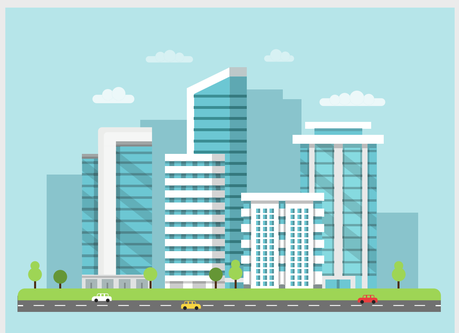
What is NER?

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.





Are those Production Ready?

What about my case?

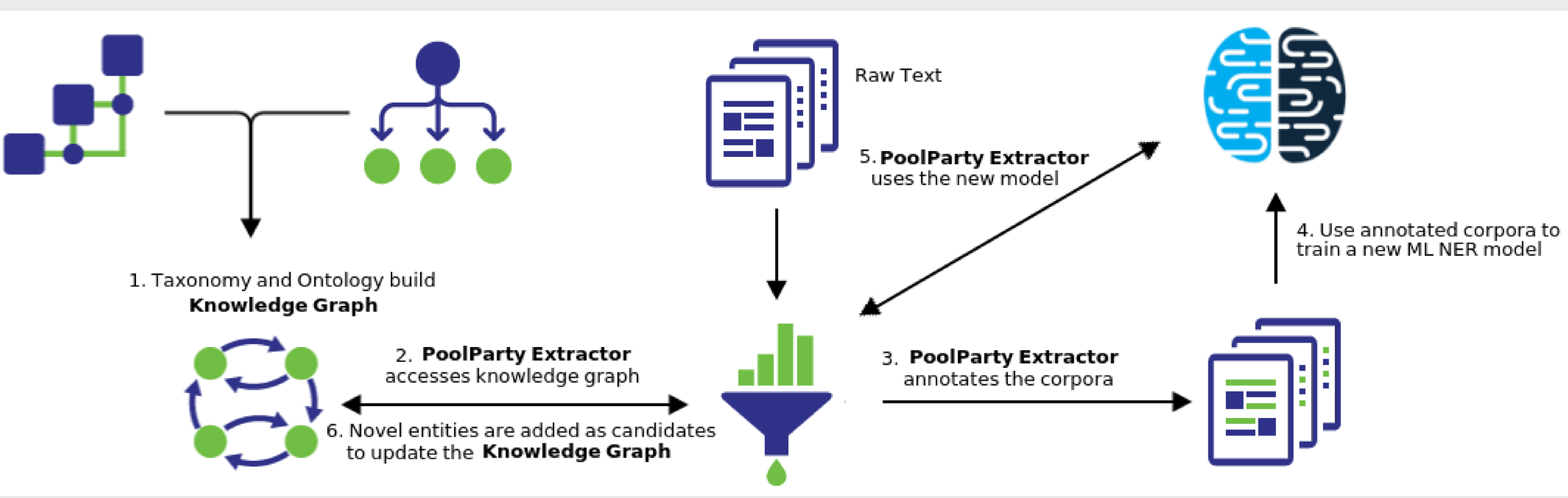
The recognition of more exotic types presents a bootstrapping problem. How can we train a classifier without the time and resource costs associated with manually annotating and curating a sizeable training dataset?

TODO:
- Case Law
- Product
- Disease

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



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 F_1 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

Dataset	Vocabulary	Entity Type	Annotation Method						ΔF_1
			Human			Automatically			
			PR	RE	F_1	PR	RE	F_1	
CoNLL-2003	Extracted	Person	96.2	86.2	90.9	90.7	72.1	80.3	-10.6
CoNLL-2003	Extracted	Location	94.9	89.1	91.9	81.2	78.3	79.8	-12.2
CoNLL-2003	Extracted	Organization	94.2	65.4	77.2	55.1	70.2	61.7	-15.5
NCBI-disease	Extracted	Disease	82.7	62.1	70.9	75.6	67.1	71.1	0.2
NCBI-disease	MeSH-2019	Disease	82.7	62.1	70.9	55.5	27.7	36.9	-34.0

Evaluation results of OpenNLP NER on human annotated test corpora. Annotation method refers to the training corpora in each case. ΔF_1 is the difference in F_1 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.

Observations

- Models trained on automatically annotated corpus can achieve comparable results to models trained on human annotated corpus;
- The process allowed us to identify common pitfalls in the automated annotation task.

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