



Supervised Distributional Hypernym Discovery via Domain Adaptation

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Motivation

- The capacity for *generalization* lies at the core of human understanding.
- Lexical taxonomies are important resources on which NLP systems rely for detecting generalizations.
 - ◆ In a taxonomy learning context, the step of hypernym discovery is crucial, and a research topic in itself.
- There are two main approaches to hypernym discovery: Path/pattern based, and distributional.



Contribution

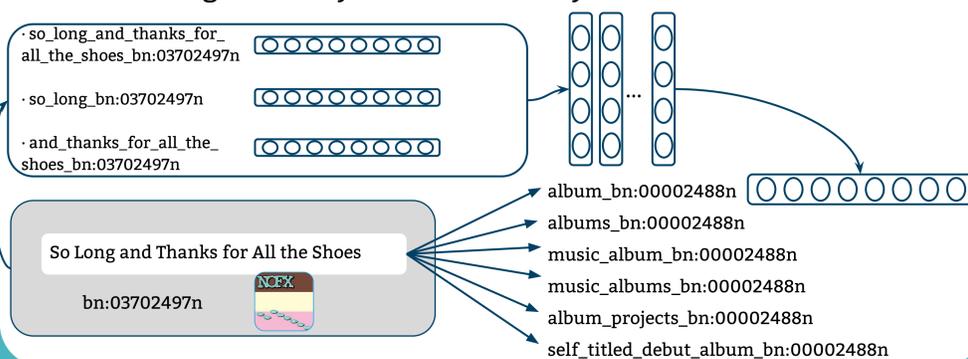
- Break down the training data in knowledge *domains* by using the distributional approach of NASARI (Camacho-Collados et al. 2016).
- Train a domain-wise *transformation matrix* (Mikolov et al. 2013), and use it to discover hypernyms.
- Improve the quality of the system by incorporating disambiguated triples coming from Open Information Extraction techniques.

Training

- Obtain *is-a* sense-level **term-hypernym pairs** from Wikidata.
- **Train a transformation matrix for each domain** such that:

$$\min_{\Psi} \sum_{i=1}^{|\Phi|} \|\Psi t_i - h_i\|^2$$

- **Apply this matrix to an unseen domain-specific term**, so that the resulting vector constitutes the “ideal” hypernym for that term. Since it may not coincide with any predefined vector, retrieve its nearest neighbours by cosine similarity.



Resources

→ **BabelNet** (Navigli and Ponzetto, 2012) - The largest multilingual repository of concepts and entities.



→ **SensEmbed** (Iacobacci et al. 2015) - A sense-level real-valued vector space representation, where each vector corresponds to a BabelNet *synset* and its *lexicalization*.
 ◆ E.g. $v(\text{bass_bn:00008917n}) = [0.2346, -0.756222, 0.123236 \dots]$



→ **KB-Unify** (Delli Bovi et al. 2015) - An integration of Open Information Extraction systems, disambiguated using BabelNet as reference sense inventory. It contains triples from Patty, WiseNet, NELL and ReVerb.



Conclusion

We perform experiments on hypernym discovery. Traditionally, systems are evaluated either on detecting a hypernymic relation in a pair of concepts, or in finding the best hypernym from a predefined and closed terminology. Providing a hypernym *from scratch* and link it to a knowledge resource is more challenging.

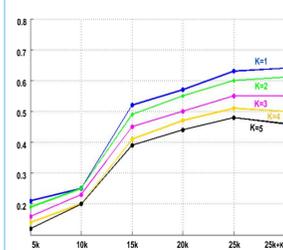
Key findings:

- **Domain clustering is essential.** This is consistent with the intuition of Fu et al. (2014).
- **In some domains, feeding OIE triples to the training data improves, but not always.**

Hypernym Discovery Evaluation

Train	education			biology			transport		
	MRR	MAP	R-P	MRR	MAP	R-P	MRR	MAP	R-P
5k	0.00	0.00	0.00	0.63	0.63	0.59	0.01	0.01	0.01
15k	0.22	0.22	0.21	0.84	0.72	0.79	0.25	0.23	0.21
25k	0.33	0.32	0.30	0.84	0.83	0.81	0.46	0.43	0.39
25k+KBU _{25k}	0.38	0.36	0.33	0.70	0.63	0.56	0.48	0.45	0.41
100k Random	0.00	0.00	0.00	0.84	0.81	0.77	0.01	0.02	0.02
Baseline	0.10	0.10	0.09	0.58	0.57	0.57	0.29	0.25	0.21

P@K- Transport



Results for other seven domains available in the paper.

Extra-Coverage

Manual evaluation **outside of Wikidata**:

- Three pattern-based comparison systems: **Yago**, **WiBi** and **DefIE**.
- Precision lower than these approaches but **competitive recall**.
- Interesting follow-up in **combining our model with pattern-based systems**, in the line of Shwartz et al. (2016).

Data & Code

- BabelNet synsets clustered by domain.
- Wikidata and KBU *isa* branches.
- Python API
 - Word, synset and sense level.
 - Batch predict and interactive console.

taln.upf.edu/taxoembed

References

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