Universität Hamburg
DER FORSCHUNG | DER LEHRE | DER BILDUNG

Alexander Panchenko, Dmitry Ustalov,
Stefano Faralli, Simone Paolo Ponzetto, and
Chris Biemann

IMPROVING HYPERNYMY EXTRACTION WITH DISTRIBUTIONAL SEMANTIC CLASSES

Introduction

Hypernyms

Examples of hypernymy relations

- **apple** –isa→ **fruit**
- **mangosteen** –isa→ **fruit**

Hypernyms

Examples of hypernymy relations

- **apple** –isa→ **fruit**
- **mangosteen** –isa→ **fruit**

Examples of applications of hypernyms

- question answering [Zhou et al., 2013]
- query expansion [Gong et al., 2005]
- semantic role labelling [Shi & Mihalcea, 2005]

Automatic extraction of hypernyms

Induction of semantic classes

Main contributions

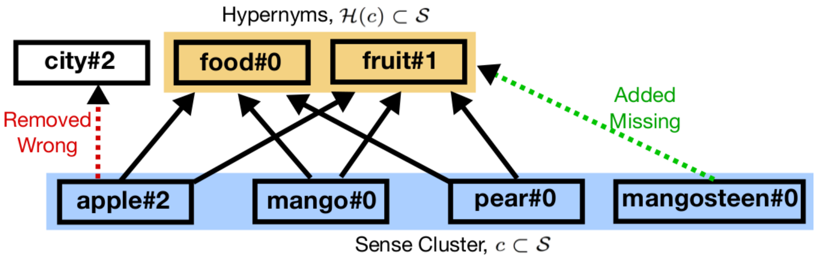
- We show how distributionally-induced **semantic classes** can be helpful for **extracting hypernyms**:

Main contributions

- We show how distributionally-induced **semantic classes** can be helpful for **extracting hypernyms**:
  1. A method for inducing sense-aware semantic classes using distributional semantics;
  2. A method for using the induced semantic classes for filtering noisy hypernymy relations.

Method

Labeled semantic classes



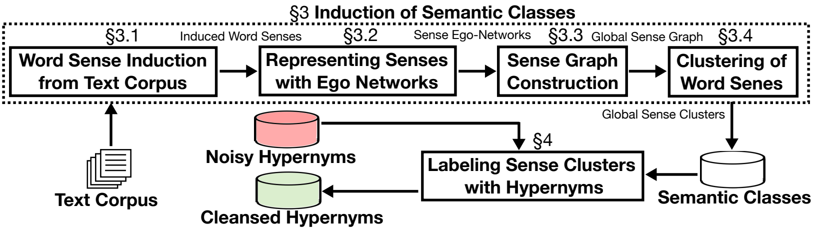
- Post-processing of hypernymy relations using distributionally induced semantic classes;
- A semantic class is a clusters of induced word senses labeled with hypernyms.

Outline of our approach

1. Sense-aware distributional semantic classes are **induced from a text corpus**;
2. Semantic classes are used to **filter a noisy hypernyms** database.

Outline of our approach

1. Sense-aware distributional semantic classes are **induced from a text corpus**;
2. Semantic classes are used to **filter a noisy hypernyms** database.



Chinese Whispers graph clustering

Used for word sense induction, used for global clustering ...

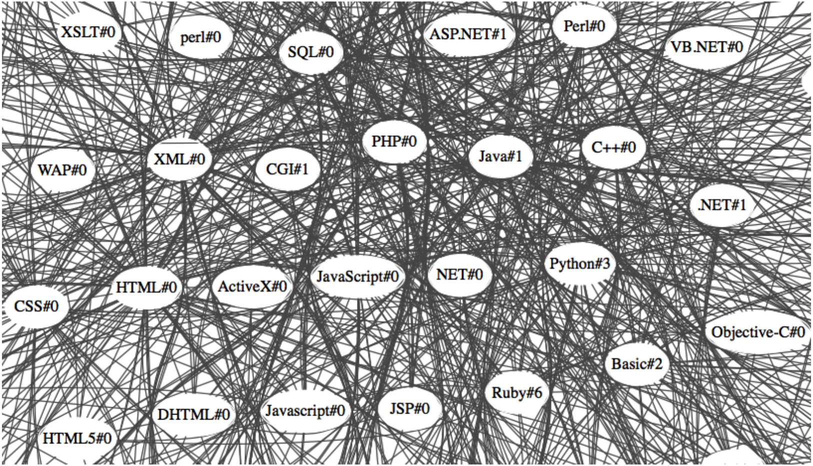
Sample of induced sense inventory

Word Sense	Local Sense Cluster: Related Senses	Hypernyms
mango#0	peach#1, grape#0, plum#0, apple#0, apricot#0, watermelon#1, banana#1, coconut#0, pear#0, fig#0, melon#0, **mangosteen#0**, ...	fruit#0, food#0, ...
apple#0	mango#0, pineapple#0, banana#1, melon#0, grape#0, peach#1, watermelon#1, apricot#0, cranberry#0, pumpkin#0, **mangosteen#0**, ...	fruit#0, crop#0, ...
Java#1	C#4, Python#3, Apache#3, Ruby#6, Flash#1, C++#0, SQL#0, ASP#2, Visual Basic#1, CSS#0, Delphi#2, MySQL#0, Excel#0, Pascal#0, ...	programming language#3, language#0, ...
Python#3	PHP#0, Pascal#0, Java#1, SQL#0, Visual Basic#1, C++#0, JavaScript#0, Apache#3, Haskell#5, .NET#1, C#4, SQL Server#0, ...	language#0, technology#0, ...

Sample of induced semantic classes

ID	Global Sense Cluster: Semantic Class	Hypernyms
1	peach#1, banana#1, pineapple#0, berry#0, blackberry#0, grapefruit#0, strawberry#0, blueberry#0, mango#0, grape#0, melon#0, orange#0, pear#0, plum#0, raspberry#0, watermelon#0, apple#0, apricot#0, watermelon#0, pumpkin#0, berry#0, **mangosteen#0**, ...	vegetable#0, fruit#0, crop#0, ingredient#0, food#0, ·
2	C#4, Basic#2, Haskell#5, Flash#1, Java#1, Pascal#0, Ruby#6, PHP#0, Ada#1, Oracle#3, Python#3, Apache#3, Visual Basic#1, ASP#2, Delphi#2, SQL Server#0, CSS#0, AJAX#0, JavaScript#0, SQL Server#0, Apache#3, Delphi#2, Haskell#5, .NET#1, CSS#0, ...	programming language#3, technology#0, language#0, format#2, app#0

Network of induced word senses



Optimization of meta-parameters

Comparison to WordNet and BabelNet

Meta-parameters

1. **Min. sense co-occurrences**: $t > 0$
2. **Sense edge weight**: count or log(count)
3. **Hypernym weight type**: tf-idf or tf

Comparison to WordNet and BabelNet

Meta-parameters

1. **Min. sense co-occurrences**: $t > 0$
2. **Sense edge weight**: count or log(count)
3. **Hypernym weight type**: tf-idf or tf

$$hpc\text{-score}(c) = \frac{h\text{-score}(c) + 1}{p\text{-score}(c) + 1} \cdot \text{coverage}(c).$$

$$p\text{-score}(c) = \frac{1}{|c|} \sum_{i=1}^{|c|} \sum_{j=1}^{i} \text{dist}(w_i, w_j). \; h\text{-score}(c) = \frac{|\mathcal{H}(c) \cap \text{gold}(c)|}{|\mathcal{H}(c)|}.$$

Best coarse- and fine-grained models

Min. sense co-occurr., t	**Edge weight**, E	**Hypernym weight**, H	**Number of clusters**	**Number of senses**	hpc-avg, **WordNet**	hpc-avg, **BabelNet**
100	log	tf-idf	734	18 028	0.092	0.304
0	count	tf-idf	1870	208 871	0.041	0.279

Results

...

• • •

• • •

• • •

...

...

• • •

...

• • •

Gong, Z., Cheang, C. W., & Leong Hou, U. (2005).
Web Query Expansion by WordNet.
In *Proceedings of the 16th International Conference on Database and Expert Systems Applications - DEXA '05* (pp. 166–175). Copenhagen, Denmark: Springer Berlin Heidelberg.

Shi, L. & Mihalcea, R. (2005).
Putting Pieces Together: Combining FrameNet, VerbNet and WordNet for Robust Semantic Parsing.
In *Proceedings of the 6th International Conference on Computational Linguistics and Intelligent Text Processing*, CICLing 2005 (pp. 100–111). Mexico City, Mexico: Springer Berlin Heidelberg.

Zhou, G., Liu, Y., Liu, F., Zeng, D., & Zhao, J. (2013).
Improving question retrieval in community question answering using world knowledge.
In *Proceedings of the Twenty-Third International Joint Conference on Artificial Intelligence*, IJCAI '13 (pp. 2239–2245). Beijing, China: AAAI Press.