Methods and Algorithms of Computational Lexical Semantics with Applications to Extraction of Senses, Hypernyms, and Frames

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14.02.2024 ♡

Outline

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- which would bridge the gap between the **precise well-interpretable** manually created lexical resources with **low coverage** and
- **less precise and non-interpretable** automatically induced from text distributional lexical representations.

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5. development of effective **vectorization** of lexical semantic graphs for the use in various application.

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10. Study of distribution of lexical semantic relations provided by neural lexical substitution models.

Content

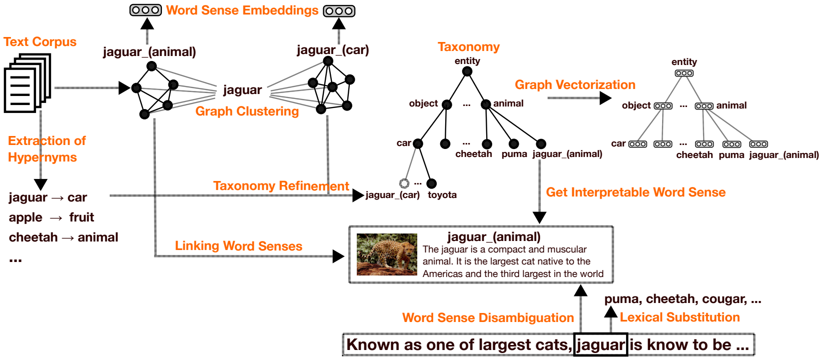

Figure: Overview of various methods for computational lexical semantics presented in this dissertation and their interrelations.

The scope of dissertation is covered in 42 publications

History

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  - The publication range from **2016** until **2023**

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  - Technical University of Darmstadt (TUDA): 2015-2016,
  - University of Hamburg (UHH): 2017-2019,
  - Skolkovo Institute of Science and Technology (Skoltech): 2019-2023,
  - Artificial Intelligence Research Institute (AIRI): 2023.

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- **8** papers indexed by **Scopus** published in workshops co-located with top conferences (CORE A*/A) [35, 17, 21, 36, 37, 38, 39, 42].

Selected 14 publications

- The defence and thesis summary is based on **14 publications** of these 42 overall published works.
- **10 first-tier** publications [1, 2, 3, 4, 5, 6, 7, 8, 9, 10] and
- **4 second-tier** publications [17, 18, 19, 20].

Research was presented at various international venues

1. **ACL-2019** [CORE A*] [3, 5, 28, 36, 13]: The 57th Annual Meeting of the Association for Computational Linguistics, (Florence, Italy)
2. **ACL-2018** [CORE A*] [10]: The 56th Annual Meeting of the Association for Computational Linguistics (Melbourne, Australia)
3. **ACL-2017** [CORE A*] [9]: The 55th Annual Meeting of the Association for Computational Linguistics (Vancouver, Canada)
4. **ACL-2016** [CORE A*] [17]: The 54th Annual Meeting of the Association for Computational Linguistics (Berlin, Germany)
5. **IJCNLP-ACL-2021** [CORE A*] [35]: The Joint Conference of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Bankok, Thailand)
6. **COLING-2022** [CORE A] [42]: The 29th International Conference on. Computational Linguistics (Gyeongju, Republic of Korea)
7. **COLING-2020** [CORE A] [2, 14]: The 28th International Conference on Computational Linguistics, (Barcelona, Spain)
8. **EACL-2017** [CORE A] [1, 4, 16, 39]: The 15th Conference of the European Chapter of the ACL (Valencia, Spain) [1]

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9. **EMNLP-2017** [CORE A] [18]: The 2017 Conference on Empirical Methods in Natural Language Processing (Copenhagen, Denmark)
10. **ISWC-2016** [CORE A] [7]: The 15th International Semantic Web Conference, (Kobe, Japan)
11. **NAACL-2019** [CORE A] [37, 38]: 2019 Annual Conference of the North American Chapter of the Association for Computational Linguistics (Minneapolis, Minnesota, USA)
12. **NAACL-2016** [CORE A] [21]: The 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (San Diego, California, USA)
13. **AACL-2022** [CORE B] [40]: The 2nd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 12th International Joint Conference on Natural Language Processing (Taipei, Taiwan)
14. **LREC-2020** [CORE B] [20]: The 12th Language Resources and Evaluation Conference, (Marseille, France)
15. **LREC-2018** [CORE B] [26, 27, 19]: The 11th International Conference on Language Resources and Evaluation (LREC 2018), (Miyazaki, Japan), European Language Resources Association (ELRA), May 2018

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16. **LREC-2016** [CORE B] [29]: The 10th International Conference on Language Resources and Evaluation (LREC16), (Portoroz, Slovenia).
17. **PaM-2020** [Scopus] [22]: The Probability and Meaning Conference (Gothenburg, Sweden)
18. **RANLP-2019** [Scopus] [33]: The International Conference on Recent Advances in Natural Language Processing (Varna, Bulgaria)
19. **GWC-2021** [Scopus] [41]: The 11th Global Wordnet Conference (Potchefstroom, South Africa)
20. **AIST-2019** [Scopus/Q2] [32]: The 8th International Conference on Analysis of Images, Social Networks and Texts (Kazan, Russia)
21. **AIST-2017** [Scopus/Q2] [30]: The 6th International Conference on Analysis of Images, Social Networks and Texts (Moscow, Russia)
22. **Dialogue-2018** [Scopus] [25, 24]: The 24th International Conference on Computational Linguistics and Intellectual Technologies (Moscow, Russia)
23. **KONVENS-2018** [Scopus] [23]: The 14th Conference on Natural Language Processing (Vienna, Austria).
24. **KONVENS-2016** [Scopus] [31]: The 13th Conference on Natural Language Processing, (Bochum, Germany)

Outline

Local-Global Graph Clustering Algorithm

- Based on publications [6, 9, 10].

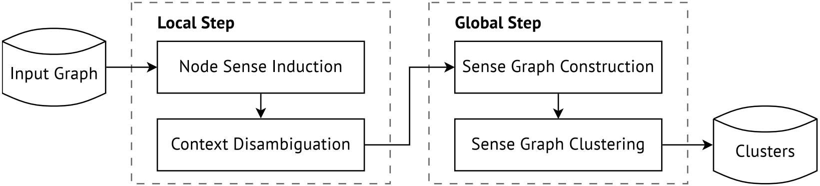

Figure: The outline of the algorithm showing the *local* step of node sense induction and context disambiguation, and the *global* step of sense graph constructing and clustering.

Local-Global Graph Clustering Algorithm

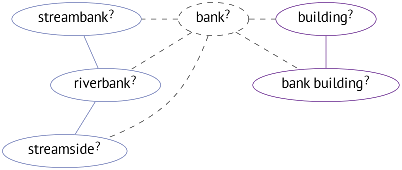

Figure: Clustering the neighborhood of the node "bank" of the input graph results in two clusters treated as the non-disambiguated sense contexts: $bank^1 = \{streambank, riverbank, \ldots\}$ and $\{bank^2 = bank\ building, building, \ldots\}$.

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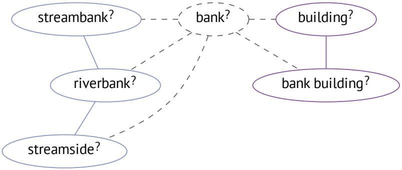

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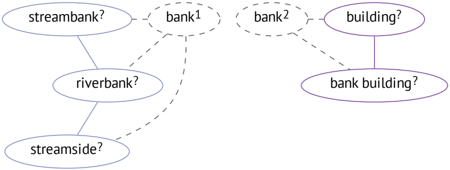

Local-Global Graph Clustering Algorithm: Watset

Input: graph $G = (V, E)$,
hard clustering algorithms $\mathrm{Cluster}_{\mathsf{Local}}$ and $\mathrm{Cluster}_{\mathsf{Global}}$,
context similarity measure $\mathrm{sim} : (\mathrm{ctx}(a), \mathrm{ctx}(b)) \to \mathbb{R}, \forall\, \mathrm{ctx}(a), \mathrm{ctx}(b) \subseteq V$.
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for all u ∈ V do                                  ▷ Local Step: Sense Induction
    senses(u) ← ∅
    V_u ← {v ∈ V : {u, v} ∈ E}                     ▷ Note that u ∉ V_u
    E_u ← {{v, w} ∈ E : v, w ∈ V_u}
    G_u ← (V_u, E_u)
    C_u ← Cluster_Local(G_u)                       ▷ Cluster the open neighborhood of u
    for all C_u^i ∈ C_u do
        ctx(u^i) ← C_u^i
        senses(u) ← senses(u) ∪ {u^i}
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    $\text{ctx}(u^i) \leftarrow C_u^i$
    $\text{senses}(u) \leftarrow \text{senses}(u) \cup \{u^i\}$
$\mathcal{V} \leftarrow \bigcup_{u \in V} \text{senses}(u)$ ▷ Global Step: Sense Graph Nodes
for all $\hat{u} \in \mathcal{V}$ **do** ▷ Local Step: Context Disambiguation
  $\widehat{\text{ctx}}(\hat{u}) \leftarrow \emptyset$
  for all $v \in \text{ctx}(\hat{u})$ **do**
    $\hat{v} \leftarrow \arg\max_{v' \in \text{senses}(v)} \text{sim}(\text{ctx}(\hat{u}) \cup \{u\}, \text{ctx}(v'))$ ▷ $\hat{u}$ is a sense of $u \in V$
    $\widehat{\text{ctx}}(\hat{u}) \leftarrow \widehat{\text{ctx}}(\hat{u}) \cup \{\hat{v}\}$
$\mathcal{E} \leftarrow \{\{\hat{u}, \hat{v}\} \in \mathcal{V}^2 : \hat{v} \in \widehat{\text{ctx}}(\hat{u})\}$ ▷ Global Step: Sense Graph Edges
$\mathcal{G} \leftarrow (\mathcal{V}, \mathcal{E})$ ▷ Global Step: Sense Graph Construction

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𝒱 ← ⋃_{u∈V} senses(u)                              ▷ Global Step: Sense Graph Nodes
for all û ∈ 𝒱 do                                   ▷ Local Step: Context Disambiguation
    ctx^(û) ← ∅
    for all v ∈ ctx(û) do
        v̂ ← arg max_{v′∈senses(v)} sim(ctx(û) ∪ {u}, ctx(v′))   ▷ û is a sense of u ∈ V
        ctx^(û) ← ctx^(û) ∪ {v̂}
ℰ ← {{û, v̂} ∈ 𝒱² : v̂ ∈ ctx^(û)}                    ▷ Global Step: Sense Graph Edges
𝒢 ← (𝒱, ℰ)                                         ▷ Global Step: Sense Graph Construction
𝒞 ← Cluster_Global(𝒢)                              ▷ Global Step: Sense Graph Clustering
C ← {{u ∈ V : û ∈ 𝒞^i} ⊆ V : 𝒞^i ∈ 𝒞}               ▷ Remove the sense labels
return C
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Local-Global Graph Clustering Algorithm: Simplified Watset*

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$\mathcal{G} \leftarrow (\mathcal{V}, \mathcal{E})$ ▷ Global Step: Sense Graph Construction
$\mathcal{C} \leftarrow \mathrm{Cluster}_{\mathsf{Global}}(\mathcal{G})$ ▷ Global Step: Sense Graph Clustering
$C \leftarrow \{\{u \in V : \hat{u} \in \mathcal{C}^i\} \subseteq V : \mathcal{C}^i \in \mathcal{C}\}$ ▷ Remove the sense labels
return C

* *Simplified version of the algorithm proposed by Dmitry Ustalov.*

Local-Global Graph Clustering Algorithm: Simplified Watset*

Table: Node sense identifier tracking in Simplified Watset.

Source	Target	Index
bank	streambank	1
	riverbank	1
	streamside	1
	building	2
	bank building	2
streambank	bank	3
	riverbank	3
...		

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Local-Global Graph Clustering Algorithm

Table: Various types of input linguistic graphs clustered by the Watset algorithm and the corresponding induced output symbolic linguistic structures.

Input Nodes	**Input Edges**	**Output Linguistic Structure**
Polysemous words	Synonymy relationships	Synsets composed of disambiguated words
Subject-Verb-Object (SVO) triples	Most distributionally similar SVO triples	Lexical semantic frames
Polysemous words	Most distributionally similar words	Semantic classes composed of disambiguated words

Outline

Word Sense Embeddings

- Based on publications [17, 20].

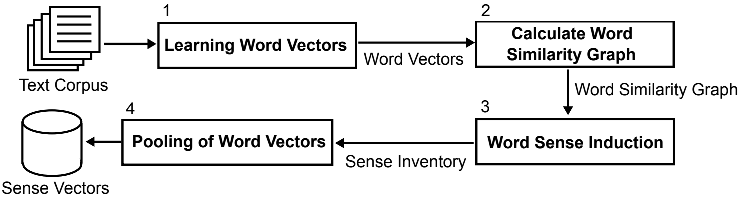

Figure: Schema of the word sense embeddings learning method "SenseGram".

Word Sense Embeddings

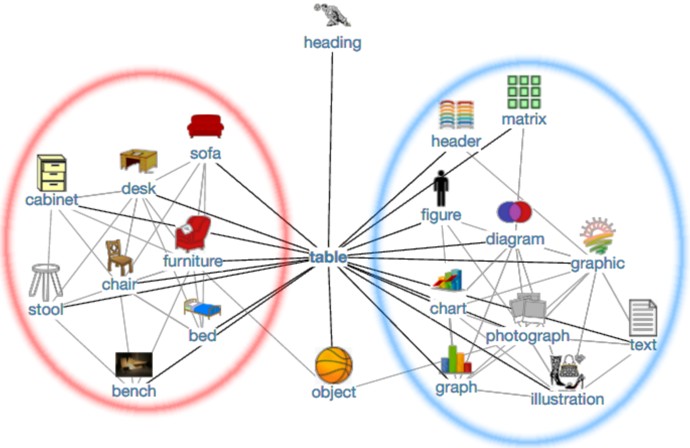

Figure: Visualization of the ego-network of "table". The target "table" is excluded from clustering.

Word Sense Induction: Baseline Algorithm

input : T – word similarity graph, N – ego-network size, n – ego-network connectivity, k – minimum cluster size
output: for each term $t \in T$, a clustering S_t of its N most similar terms

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    G ← graph with V as nodes and no edges E
    foreach v ∈ V do
        V′ ← n most similar terms of v from T
        foreach v′ ∈ V′ do
            if v′ ∈ V then add edge (v, v′) to E
        end
    end
```

Word Sense Induction: Baseline Algorithm

input : T – word similarity graph, N – ego-network size, n – ego-network connectivity, k – minimum cluster size

output: for each term $t \in T$, a clustering S_t of its N most similar terms

foreach $t \in T$ **do**
    $V \leftarrow N$ most similar terms of t from T
    $G \leftarrow$ graph with V as nodes and no edges E
    foreach $v \in V$ **do**
        $V' \leftarrow n$ most similar terms of v from T
        foreach $v' \in V'$ **do**
            if $v' \in V$ **then** add edge (v, v') to E
        end
    end
    $S_t \leftarrow \texttt{ChineseWhispers}(G)$
    $S_t \leftarrow \{s \in S_t : |s| \geq k\}$
end

Word Sense Induction: Improved Graph Construction

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   - $w = python$, its top similar term $w_1 = Java$ and the anti-node $\overline{w_i} = snake$ form an anti-edge $(w_i, \overline{w_i}) = (Java, snake)$.

Word Sense Induction: Improved Graph Construction

4. Construct graph $G = (V, E)$ from the list of anti-edges $\overline{E}$, with the following recurrent procedure:
$V = V \cup \{w_i, \overline{w_i} : w_i \in \mathcal{N}, \overline{w_i} \in \mathcal{N}\}$

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   - Do not add edges corresponding to anti-nodes if any.

Word Sense Embeddings

Vector	Nearest Neighbours
table	tray, bottom, diagram, bucket, brackets, stack, basket, list, parenthesis, cup, trays, pile, playfield, bracket, pot, drop-down, cue, plate
table#0	leftmost#0, column#1, randomly#0, tableau#1, top-left#0, indent#1, bracket#3, pointer#0, footer#1, cursor#1, diagram#0, grid#0
table#1	pile#1, stool#1, tray#0, basket#0, bowl#1, bucket#0, box#0, cage#0, saucer#3, mirror#1, birdcage#0, hole#0, pan#1, lid#0

Table: Neighbours of the word "table" and its senses produced by our method. The neighbours of the initial vector belong to both senses, while those of sense vectors are sense-specific.

Word Sense Embeddings

- **Get Sense Embeddings by pooling of word vectors**:
  $$\mathbf{s}_i = \frac{\sum_{w \in S_t} \gamma_i(w_k) vec_w(w_k)}{\sum_{s \in S_t} \gamma_i(w_k)}.$$

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  $$s^* = \arg\max_i sim(\mathbf{s}_i, C) = \arg\max_i \frac{\bar{\mathbf{c}}_w \cdot \mathbf{s}_i}{\|\bar{\mathbf{c}}_w\| \cdot \|\mathbf{s}_i\|},$$
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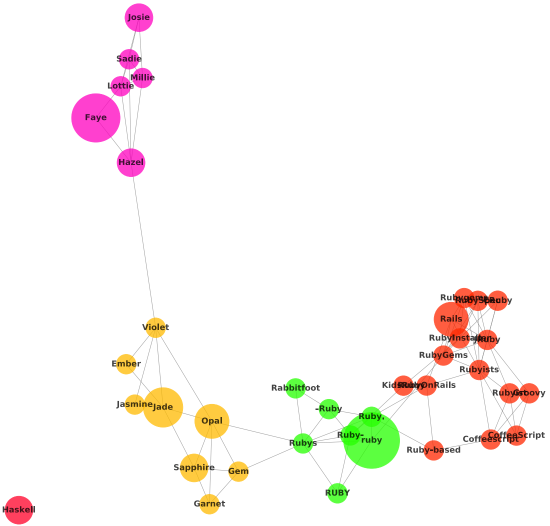
- **Knowledge-Free Labelling of Induced Sense Clusters**:
  $$keyness(v) = |\{(w_i, \overline{w_i}) : (w_i, \overline{w_i}) \in \overline{E} \wedge (v = w_i \vee v = \overline{w_i})\}|,$$
  .. is number of anti-edges among words in this cluster.

Word Sense Embeddings



Outline

Unsupervised Interpretable Word Sense Disambiguation

- Based on publications [1] and [18].

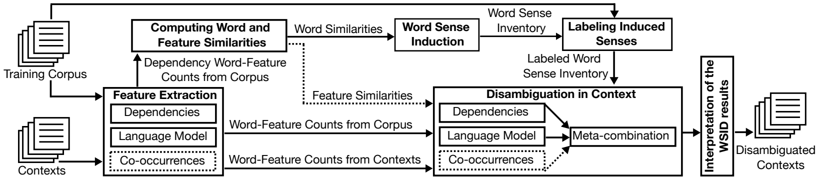


Figure: Outline of unsupervised interpretable method for word sense induction and disambiguation.

Unsupervised Interpretable Word Sense Disambiguation

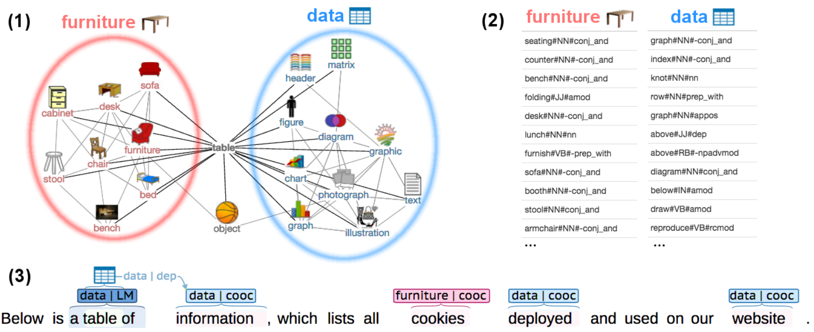


Figure: Interpretation of the senses of the word "table" at three levels: (1) word sense inventory; (2) sense feature representation; (3) results of disambiguation in context. The sense labels ("furniture" and "data") are obtained automatically based on cluster labeling with hypernyms. The images associated with the senses are retrieved using a search engine: "table data" and "table furniture".

Unsupervised Interpretable Word Sense Disambiguation

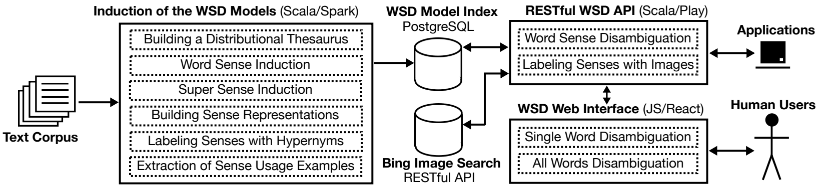
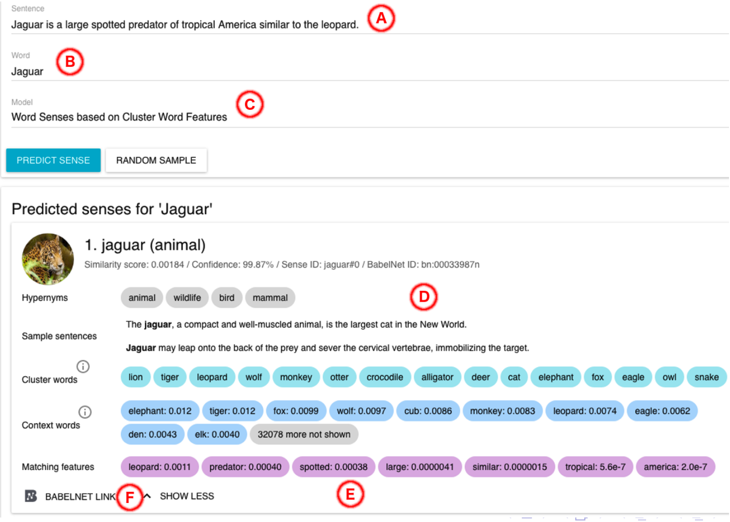


Figure: Software and functional architecture of the WSD system.

Unsupervised Interpretable Word Sense Disambiguation



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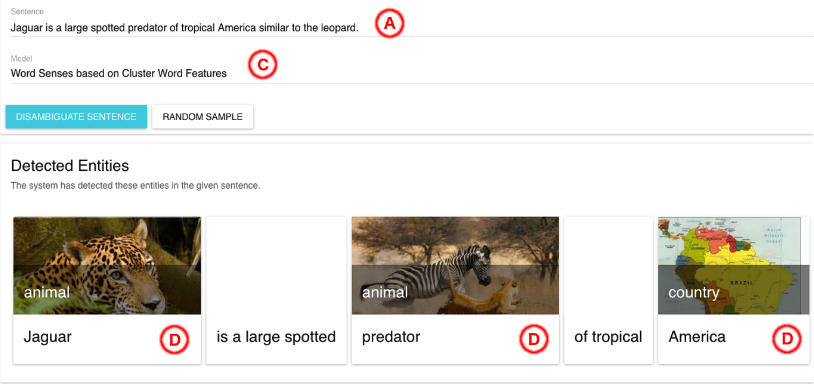

Outline

Linking Word Sense Representations

- Based on publications [7, 8].

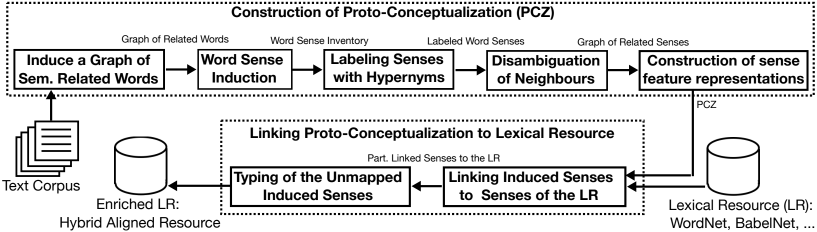

Figure: Overview of gtthe proposed framework for enriching lexical resources: a distributional semantic model is used to construct a disambiguated distributional lexical semantic network (a proto-conceptualization, PCZ), which is subsequently linked to the lexical resource.

Linking Word Sense Representations

1. **LR** W: lexical resource e.g. WordNet or BabelNet;

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5. Compare the two senses with similarity function:

$$sim(j, c, M) = \frac{|T.BoW(j, M, W) \cap W.BoW(c)|}{|T.BoW(j, M, W)|},$$

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for $step = 1$; $step \leq m$; $step = step + 1$ **do**
    $M_{step} = \emptyset$
    for all $(j_i, R_{j_i}, H_{j_i}) \in T.senses / M.senses$ **do**
        $C(j_i) = W.getSenses(j_i.lemma, j_i.POS)$
        for all $c_k \in C(j_i)$ **do**
            $rank(c_k) = sim(j_i, c_k, M)$
        if $rank(c_k)$ has a single top value for c_t **then**
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  $M = M \cup \{(j_i, j_i)\}$
return M

Linking Word Sense Representations

PCZ ID	WordNet ID	PCZ Related Terms	PCZ Context Clues
mouse:0	mouse:wn1	rat:0, rodent:0, monkey:0, ...	rat:conj_and, gray:amod, ...
mouse:1	mouse:wn4	keyboard:1, computer:0, printer:0 ...	click:-prep_of, click:-nn, ...
keyboard:0	keyboard:wn1	piano:1, synthesizer:2, organ:0 ...	play:-dobj, electric:amod, ..
keyboard:1	keyboard:wn1	keypad:0, mouse:1, screen:1 ...	computer, qwerty:amod ...

Table: Sample entries of the hybrid aligned resource (HAR) for the words *mouse* and *keyboard*. Trailing numbers indicate sense identifiers. To enrich WordNet sense representations we rely on related terms and context clues.

Outline

Prediction of Hypernym Embeddings

- Based on publications [4].

Introduction

- **Hypernymy** represent hierarchical relations between terms:
  - (apple, **is-a**, fruit): apple = **hypo**nym, fruit = **hyper**nym;
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  - a square matrix $\mathbf{\Phi}^*$ is fit
  - on the training set of positive pairs $\mathcal{P}$:

$$\mathbf{\Phi}^* = \arg\min_{\mathbf{\Phi}} \frac{1}{|\mathcal{P}|} \sum_{(\vec{x},\vec{y})\in\mathcal{P}} \left\| \vec{x}\mathbf{\Phi} - \vec{y} \right\|^2 ,$$

Prediction of Hypernym Embeddings

Hypernymy extraction via **regularized** projection learning.

- Linguistic Constraints via Regularization

$$\mathbf{\Phi}^* = \arg\min_{\mathbf{\Phi}} \frac{1}{|\mathcal{P}|} \sum_{(\vec{x},\vec{y}) \in \mathcal{P}} \|\vec{x}\mathbf{\Phi} - \vec{y}\|^2 + \lambda R,$$

- **Asymmetric Regularization.** Enforces the asymmetry: the same transformation to the predicted hypernym should not provide a vector similar to the initial hyponym:

$$R = \frac{1}{|\mathcal{P}|} \sum_{(\vec{x},\_) \in \mathcal{P}} (\vec{x}\mathbf{\Phi}\mathbf{\Phi} \cdot \vec{x})^2.$$

Prediction of Hypernym Embeddings

Hypernymy extraction via **regularized** projection learning.

- **Neighbor Regularization.** Negative sampling by explicitly providing the examples of semantically related words $\vec{z}$ of the hyponym $\vec{x}$: penalizes the model to produce similar vectors:

$$R = \frac{1}{|\mathcal{N}|} \sum_{(\vec{x},\vec{z}) \in \mathcal{N}} (\vec{x}\mathbf{\Phi}\mathbf{\Phi} \cdot \vec{z})^2.$$

- We use synonyms of hyponyms as $\mathcal{N}$
- **Regularizers without Re-Projection.** The neighbor regularizer:

$$R = \frac{1}{|\mathcal{N}|} \sum_{(\vec{x},\vec{z}) \in \mathcal{N}} (\vec{x}\mathbf{\Phi} \cdot \vec{z})^2.$$

Outline

Extracting of Hypernyms via Sense Graph Clustering

- Based on publication [19].

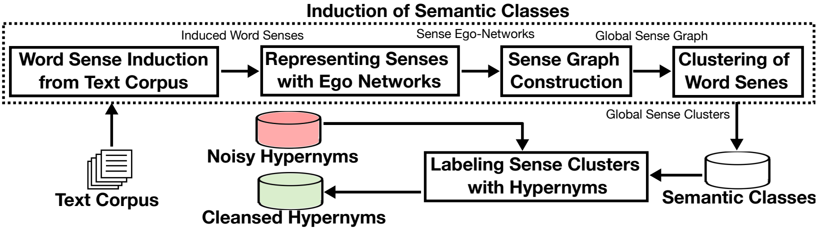

Figure: Outline of the approach: sense-aware distributional semantic classes are induced from a text corpus and then used to filter noisy hypernyms database (e.g. extracted by an external method from a text corpus).

Extracting of Hypernyms via Sense Graph Clustering

Global Sense Cluster: Semantic Class, $c \subset \mathcal{S}$	**Hypernyms,** $\mathcal{H}(c) \subset \mathcal{S}$
peach#1, banana#1, pineapple#0, berry#0, blackberry#0, grapefruit#0, strawberry#0, blueberry#0, fruit#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, ·
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

Table: Sample of the induced sense clusters representing “fruits” and “programming language” semantic classes.

Extracting of Hypernyms via Sense Graph Clustering

Representing Senses with Ego Networks

1. Represent each induced sense s by a second-order **ego network** consisting of related senses $\mathcal{R}(s)$ of the ego sense s:

$$\{s_j : (s_j \in \mathcal{N}(s)) \vee (s_i \in \mathcal{N}(s) \wedge s_j \in \mathcal{N}(s_i))\}.$$

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2. Edge weight $\mathcal{W}_s(s_i, s_j)$ between two senses is equal to a distributional semantic relatedness score between s_i and s_j.
3. Cluster each ego network and discard networks for which the cluster containing the target sense s contains less than 80% nodes of the respective network to ensure semantic coherence.

Extracting of Hypernyms via Sense Graph Clustering

Global Sense Graph Construction

1. Compute weights of the edges of the global graph by counting the number of co-occurrences of the edge in ego networks:

$$\mathcal{W}(s_i, s_j) = \sum_{s \in \mathcal{S}} \mathcal{W}_s(s_i, s_j).$$

2. To filter noisy edges and re-scale weights:

$$\mathcal{W}(s_i, s_j) = \begin{cases} \log \mathcal{W}(s_i, s_j) & \text{if } \mathcal{W}(s_i, s_j) \geq t, \\ 0 & \text{otherwise.} \end{cases}$$

Extracting of Hypernyms via Sense Graph Clustering

Clustering of Word Senses

- **Fine-grained**: 208,871 word senses ⇒ 1,870 semantic classes,
- **Coarse-grained**: 18,028 word senses ⇒ 734 semantic classes.

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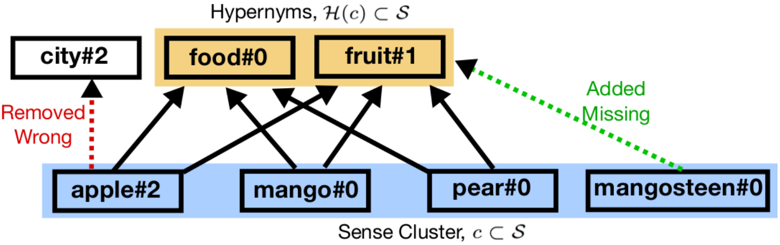
Denoising Hypernyms using the Distributional Semantic Classes

- Sense cluster is labeled with top 5 common hypernyms.
- For labeling we used the tf–idf weighting:

$$\text{tf–idf}(h) = \sum_{s \in c} \mathcal{H}(s) \cdot \log \frac{|\mathcal{S}|}{|h \in \mathcal{H}(s) : \forall s \in \mathcal{S}|},$$

where $\sum_{s \in c} \mathcal{H}(s)$ is a sum of weights for all hypernyms s.

Extracting of Hypernyms via Sense Graph Clustering



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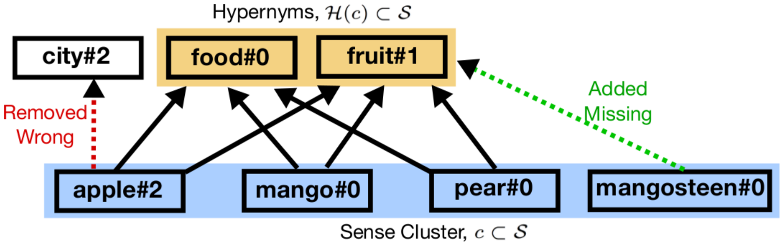

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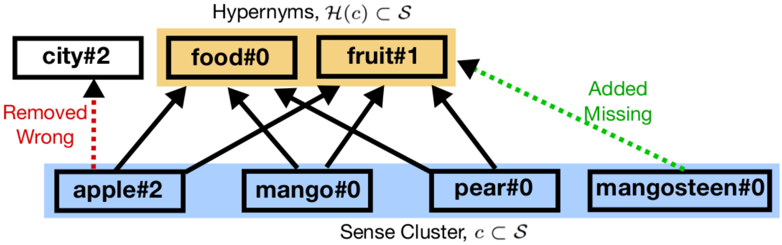

- Post-processing of hypernymy relations using distributionally induced semantic classes, represented by clusters of induced word senses labeled with noisy hypernyms.
- Wrong hypernyms outside the cluster labels are removed, while the missing ones not present in the noisy database of hypernyms are added.

Outline

Taxonomy Enrichment using Hyperbolic Embeddings

- Based on publication [5].

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  - **Removing wrong** edges: $E = E \setminus E_{wrg}$
  - For orphan nodes only adding edges is needed
  - For connected nodes either
    - Adding absent additional edge is needed or
    - **Relocation** i.e. a combination of removing wrong with adding absent edge(s) is needed.

Taxonomy Enrichment using Hyperbolic Embeddings

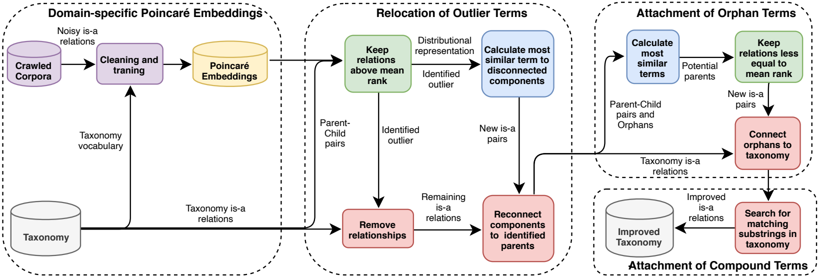

Figure: Outline of the taxonomy refinement method.

Taxonomy Enrichment using Hyperbolic Embeddings

Hypernym-Hyponym Distance

- Poincaré embeddings are trained on extracted from text IS-A relations or WordNet.

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Taxonomy Enrichment using Hyperbolic Embeddings

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4. Previously or now disconnected isolated nodes are subject to orphan attachment.
5. Compute distance to the closest co-hyponym for every node to identify and relocate outliers.

Taxonomy Enrichment using Hyperbolic Embeddings

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3. For Euclidean embeddings, a link is added between the parent of the most similar co-hyponym and the orphan.

Taxonomy Enrichment using Hyperbolic Embeddings

Word	**Parent patterns**	**Parent after refinement**	**Gold parent**	**Closest neighbors**
second language acquisition	—	linguistics	linguistics	applied linguistics, semantics, linguistics
botany	—	genetics	plant science, ecology	genetics, evolutionary ecology, animal science
sweet potatoes	—	vegetables	vegetables	vegetables, side dishes, fruit
wastewater	water	waste	waste	marine pollution, waste, pollutant
water	waste, natural resources	natural resources	aquatic environment	continental shelf, management of resources
international relations	sociology, analysis, humanities	humanities	political science	economics, economic theory, geography

Table: Example words with respective parent(s) in the input taxonomy constructed using Hearst' patterns approach and after refinement using our domain-specfic Poincaré embeddings, as well as the word's closest three neighbors (incl. orphans) in embeddings.

Outline

Node Embeddings of Lexical-Semantic Graphs

- Based on publication [3].

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- Custom **graph node similarity measures** $sim : V \times V \to \mathbb{R}$ have been defined on pairs of nodes V of a graph $G = (V, E)$.

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- Computing directly on the graph can be prohibitively computationally expensive.

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- ... and all their respective adjacent nodes $\{v_n : \exists(v_i, v_n) \in E\}$ and $\{v_m : \exists(v_j, v_m) \in E\}$ to preserve local structure of the graph.

Node Embeddings of Lexical-Semantic Graphs

- The path2vec model preserves both global and local relations between nodes by minimizing

$$\mathcal{L} = \sum_{(v_i, v_j) \in B} ((\mathbf{v}_i^\top \mathbf{v}_j - s_{ij})^2 - \alpha(\mathbf{v}_i^\top \mathbf{v}_n + \mathbf{v}_j^\top \mathbf{v}_m)),$$

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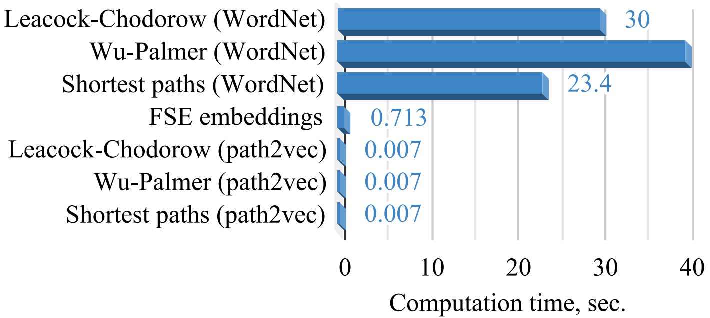

Figure: Similarity computation: graph vs vectors.

Node Embeddings of Lexical-Semantic Graphs

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- Such pruning does not lead to loss of effectiveness.

Outline

Lexical Substitution and Analysis of Semantic Relations

Lexical Substitution with LMs

1. Build our substitute probability estimators using LMs/MLMs $P(s|C)$: ELMo [44], BERT [45], XLNet [46], etc.
2. Combine a distribution provided by a context-based substitute probability estimator $P(s|C)$ with a distribution based on the proximity of possible substitutes to the target:

$$P(s|T) \propto \exp\left(\frac{\langle emb_s, emb_T \rangle}{\mathcal{T}}\right).$$

3. The final distribution is obtained by the formula:

$$P(s|C,T) \propto \frac{P(s|C)P(s|T)}{P(s)^{\beta}}.$$

Lexical Substitution and Analysis of Semantic Relations

- Based on publication [2].

We were not able to travel in the weather , and there was no ***phone*** .										
GOLD	**telephone (5)**									
OOC	phone	**telephone**	phones	cellphone	fone	videophone	handset	telephones	p990i	cell-phone
XLNet	electricity	internet	phone	power	**telephone**	car	water	communication	radio	tv
XLNet+embs	phone	**telephone**	phones	cellphone	internet	radio	electricity	iphone	car	computer
What happened to the big , new garbage ***can*** at Church and Chambers Streets ?										
GOLD	**bin (4)**	**disposal (1)**	**container (1)**							
OOC	can	could	should	would	will	must	might	to	may	ll
XLNet	can	dump	**bin**	truck	**disposal**	pit	heap	pile	**container**	stand
XLNet+embs	can	could	will	**bin**	cannot	dump	may	truck	**disposal**	stand

Types of semantic relations: synonym co-hyponym co-hyponym 3 target
direct hypernym transitive hypernym
direct hyponym transitive hyponym unknown-relation unknown-word

Figure: Examples of top substitutes provided by annotators (GOLD), the baseline (OOC), and two presented models (XLNet and XLNet+embs). The target word in each sentence is in bold, true positives are in bold also. The weights of gold substitutes are given in brackets. Each substitute is colored according to its lexical-semantic relation to the target word.

Lexical Substitution and Analysis of Semantic Relations

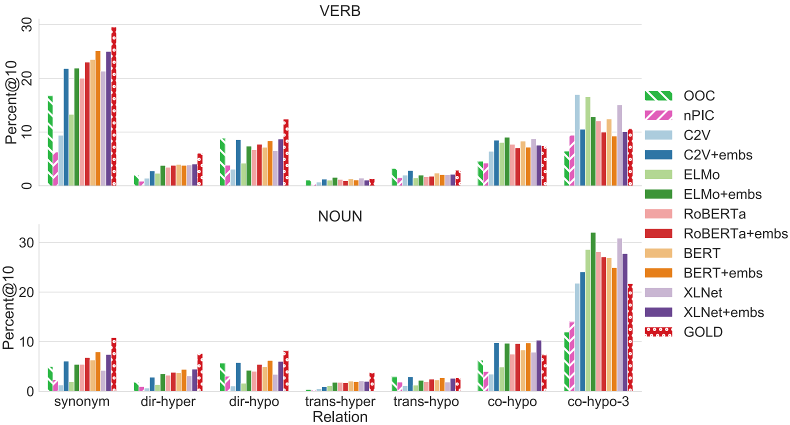

Figure: Proportions of substitutes related to the target by various semantic relations according to WordNet.

Outline

Summary

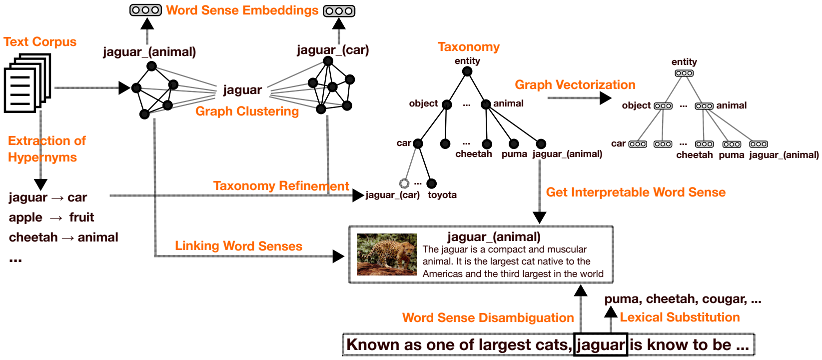

Figure: Overview of various methods for computational lexical semantics presented in this dissertation and their interrelations.

Acknowledgements

- **Christian Biemann** as the main advisor and supporter.
- Key co-authors: **Dmitry Ustalov**, **Nikolay Arefyev**, **Simono Paolo Ponzetto**, **Stefano Faralli**, and **Andrey Kutuzov**.
- Student co-authors: Ramy Aly, Maria Pelevina, Shantanu Acharya, Eugen Ruppert, Boris Sheludko, Mohamman Dorgham, Oleksiy Oliynyk, Alexander Ossa, Arne Kohn, Yuri Arkihpov, Saba Anwar, and Özge Sevgili.
- Yuri Nikolaevich Philippovich and Cédrick Fairon for introducing me into CL, NLP and research in general.
- Colleagues helped and encouraged in manuscript preparation: Elena Gryazina and Elena Tutubalina.
- My family: Luidmila Borisovna, Ivan Ivanovich, Polina, Evgenii, and Konstantin.

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