Methods of Computational Lexical Semantics for Extraction, Linking, Vectorization, and Disambiguation

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01.03.2024

Outline

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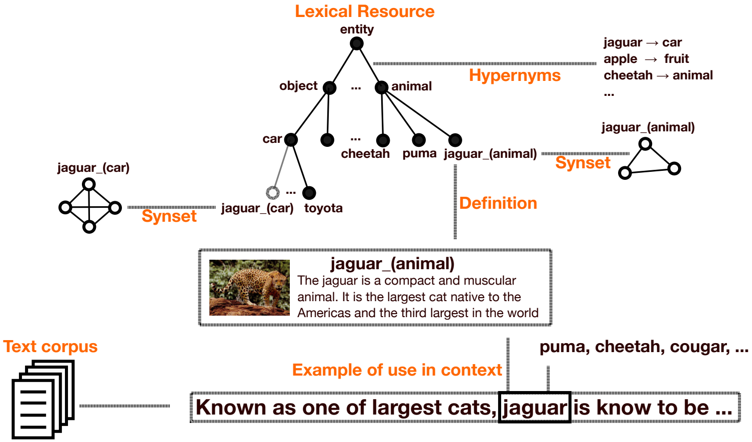
Outline

Object of Lexical Semantics



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- **precise** and **interpretable** manually created lexical resources with **low coverage**, e.g. taxonomies or WordNets
- **noisy** and **non-interpretable** automatically induced from text distributional lexical representations with **high coverage**, e.g. distributional thesauri or word embeddings

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

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

Content

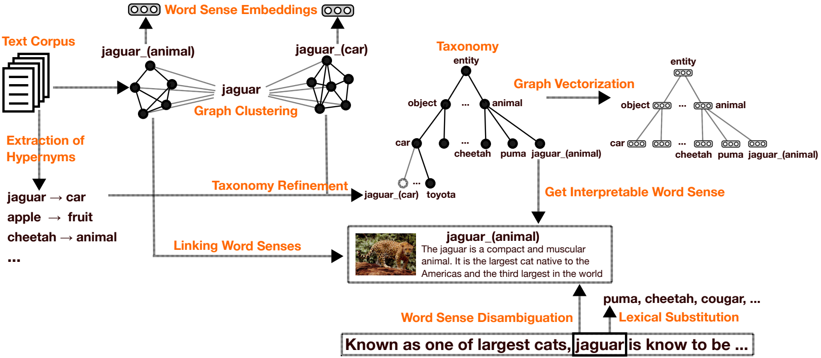

Figure: Overview of various methods for computational lexical semantics presented in this dissertation and their interrelations.

History of research behind this dissertation

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

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

The scope of dissertation is covered in 42 publications

- **5** papers are published in **CORE A***
  conferences [3, 5, 9, 10, 13];
- **6** papers are published in **CORE A** conferences [1, 2, 4, 7, 16];
- **5** articles are published in in **Q1** journals [6, 8, 11, 12, 15];
- **1** paper is published in **CORE A*** conference student track [28];
- **1** paper is published in **CORE A** conference demo track [18];
- **5** papers is published at **CORE B** conference [20, 26, 19, 27, 29];
- **11** papers indexed by **Scopus** published in proceedings of the main volumes of conferences [22, 23, 24, 25, 30, 31, 32, 33, 34, 40, 41];
- **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 (LREC'16), (Portoroˇz, 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)

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Local-Global Graph Clustering Algorithm

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

Task Definition: Graph Clustering

- Let $G = (V, E)$ be an undirected simple **graph**, where V is a set of nodes and $E \subseteq V^2$ is a set of undirected edges.

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- A **graph clustering** is a function $\textsc{Cluster} : (V, E) \to C$ such that $V = \bigcup_{C^i \in C} C^i$.
- Two classes of graph clustering exist: **hard clustering** algorithms (partitionings) produce non-overlapping clusters, i.e., $C^i \cap C^j = \emptyset \iff i \neq j, \forall C^i, C^j \in C$
- While **fuzzy clustering** permit cluster overlapping, i.e., a node can be a member of several clusters in C.

Local-Global Graph Clustering Algorithm

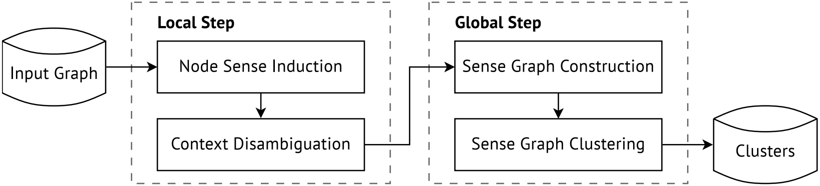

Figure: The outline of the algorithm showing the *local* step of node sense induction and context disambiguation, and the *global* step of sense graph constructing and clustering.

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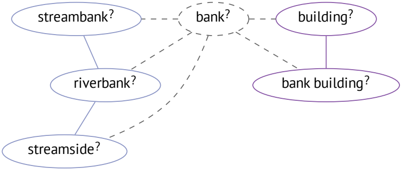

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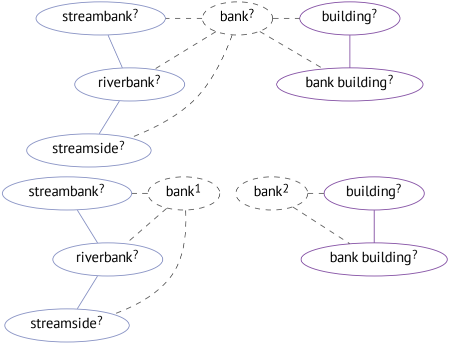

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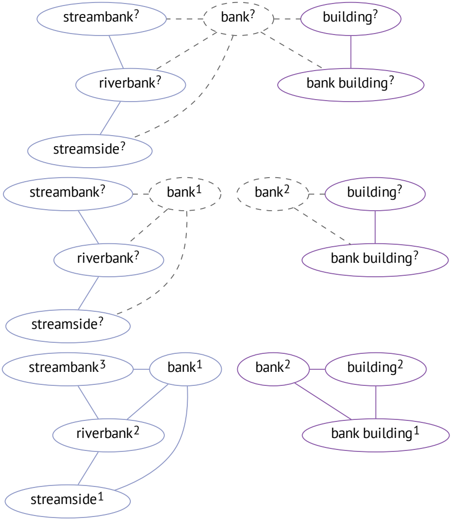

Local-Global Graph Clustering Algorithm: Watset

Input: graph $G = (V, E)$,
hard clustering algorithms $\mathrm{Cluster}_{\mathsf{Local}}$ and $\mathrm{Cluster}_{\mathsf{Global}}$,
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  for all $C_u^i \in C_u$ **do**
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return C

Local-Global Graph Clustering Algorithm: Simplified Watset*

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* *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

Sample synsets induced by the Watset[MCL, MCL] method

Size	Synset
2	decimal point, dot
2	wall socket, power point
3	gullet, throat, food pipe
3	CAT, computed axial tomography, CT
4	microwave meal, ready meal, TV dinner, frozen dinner
4	mock strawberry, false strawberry, gurbir, Indian strawberry
5	objective case, accusative case, oblique case, object case, accusative
5	discipline, sphere, area, domain, sector
6	radio theater, dramatized audiobook, audio theater, radio play, radio drama, audio play
6	integrator, reconciler, consolidator, mediator, harmonizer, uniter
7	invite, motivate, entreat, ask for, incentify, ask out, encourage
7	curtail, craw, yield, riding crop, harvest, crop, hunting crop

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Word Sense Embeddings

- Based on publications [17, 20].

Task formulation

- **Input:**
  - Set of word vectors of an ambiguous vocabulary V: $\forall v \in V$ $\exists \mathbf{v} \in \mathbb{R}^d$, where d is dimensionality of vector space.

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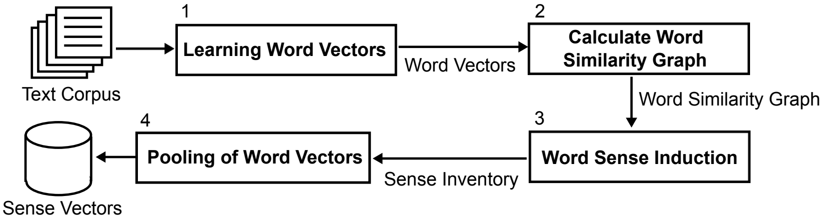
- **Output:**
  - Word sense inventory S: $\forall v \in V$ $\exists S = \{s_1, ..., s_k\} : s_i \subset V$, where k is the number of senses of word v.
  - Word sense vectors: $\forall s_i$ $\exists \mathbf{s}_i \in \mathbb{R}^d$

"SenseGram" Word Sense Embeddings Method



Word Sense Induction

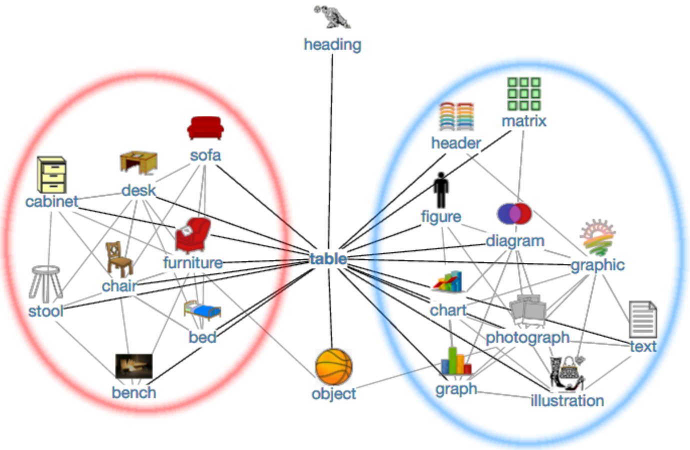


Figure: Visualization of the ego-network of “table”. The target “table” is excluded from clustering.

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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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foreach t ∈ T do
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    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
```

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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

Graph Construction with EGVI (Ego-Graph Vector Induction)

1. Extract a list $\mathcal{N} = \{w_1, w_2, ..., w_N\}$ of N nearest neighbours for the target (ego) word vector w.

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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 $(w_i, \overline{w_i}) = (Java, snake)$.

Graph Construction with EGVI (Ego-Graph Vector Induction)

4. Construct graph $G = (V, E)$ from the list of anti-edges $\overline{E}$, with the following recurrent procedure:
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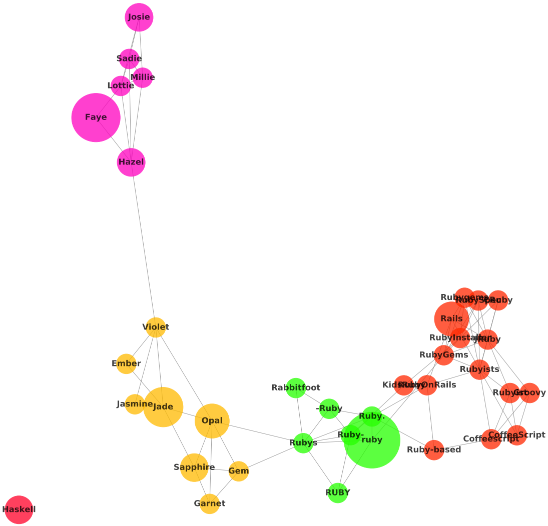
   - Do not add edges corresponding to anti-nodes if any.

Word Sense Embeddings of the word “Ruby”



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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- **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.

Nearest Neighbours of Word and 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.

Outline

Unsupervised Interpretable Word Sense Disambiguation

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

Task formulation

- **Input:**
  - Word sense inventory S
  - Mention of a word v in a context C.
- **Output:**
  - Word sense of the word v corresponding to the context C.
  - Human-readable interpretation of the sense s.

Outline of the Method

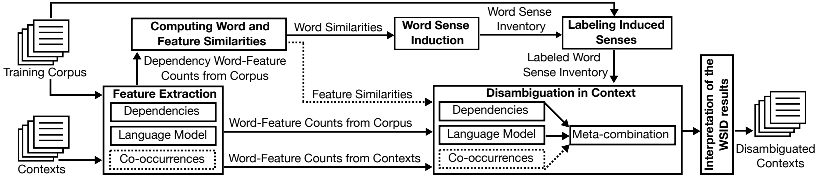
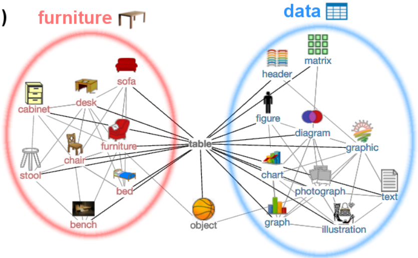


Figure: Unsupervised interpretable method for word sense induction and disambiguation.

Unsupervised Interpretable Word Sense Disambiguation

(1)



(2)

furniture	data
seating#NN#conj_and	graph#NN#-conj_and
counter#NN#-conj_and	index#NN#-conj_and
bench#NN#-conj_and	knot#NN#nn
folding#JJ#amod	row#NN#prep_with
desk#NN#-conj_and	graph#NN#appos
lunch#NN#nn	above#JJ#dep
furnish#VB#-prep_with	above#RB#-npadvmod
sofa#NN#-conj_and	diagram#NN#conj_and
booth#NN#-conj_and	below#IN#amod
stool#NN#conj_and	draw#VB#amod
armchair#NN#-conj_and	reproduce#VB#rcmod
...	...

(3)

data | dep

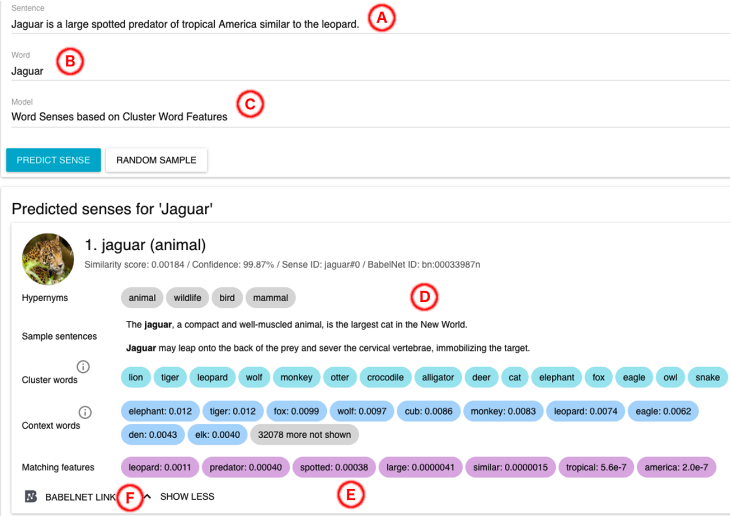
data | LM — data | cooc — furniture | cooc — data | cooc — data | cooc

Below is a table of information, which lists all cookies deployed and used on our website .

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.

Unsupervised Interpretable Word Sense Disambiguation



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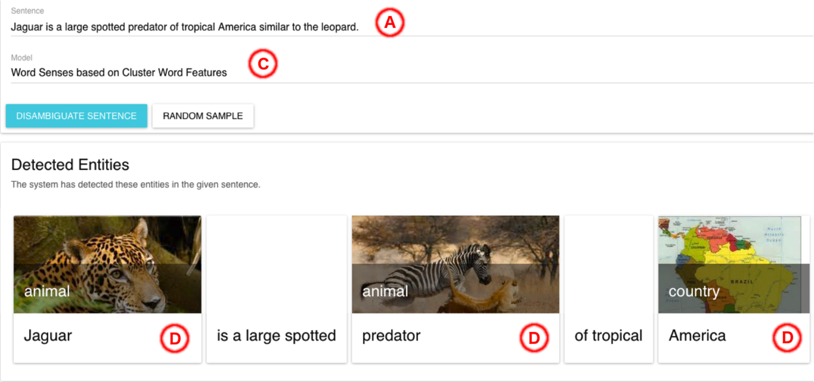

Outline

Linking Word Sense Representations

- Based on publications [7, 8].

Task Definition: Sense Linking

Input:

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

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  - j_i is a sense identifier, i.e. mouse:1,
  - R_{j_i} the set of its semantically related senses, i.e. $R_{j_i} = \{$keyboard:1, computer:0, $\ldots\}$,
  - H_{j_i} the set of its hypernym senses, i.e. $\{$equipment:3$, \ldots\}$.

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Output:

- **Mapping** M: set of pairs of the kind $(source, target)$ where $source \in T.senses$ is a sense of the input PCZ T and $target \in W.senses \cup source$ is the most suitable sense of W.

Overview of the Framework for Enriching Lexical Resources

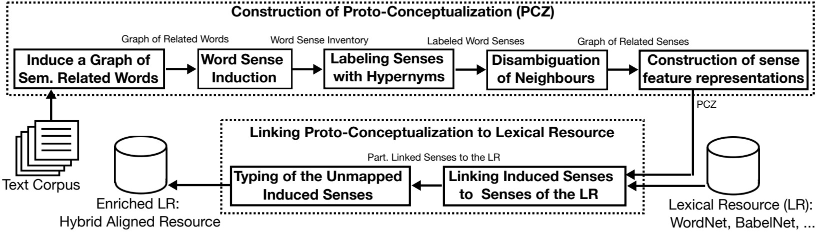

Figure: A distributional semantic model is used to construct a disambiguated distributional lexical semantic network (a proto-conceptualization, PCZ), which is subsequently linked to the lexical resource (LR).

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  for all $(j_i, R_{j_i}, H_{j_i}) \in T.monosemousSenses$ **do**
    $C(j_i) = W.getSenses(j_i.lemma, j_i.POS)$
    if $|C(j_i)| == 1$, let $C(j_i) = \{c_0\}$ **then**
      if $sim(j_i, c_0, \emptyset) \geq th$ **then**
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for $step = 1$; $step \leq m$; $step = step + 1$ **do**
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  for all $(j_i, R_{j_i}, H_{j_i}) \in T.senses / M.senses$ **do**
    $C(j_i) = W.getSenses(j_i.lemma, j_i.POS)$
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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].

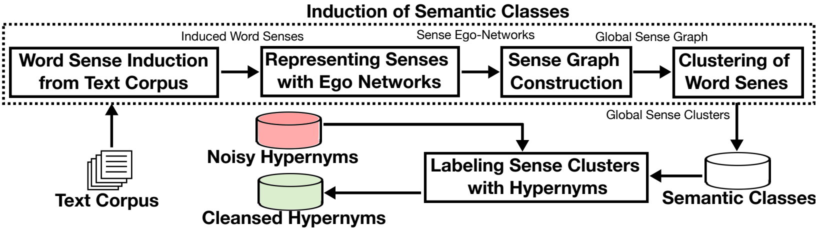

Figure: Sense-aware distributional semantic classes are induced from a text corpus and then used to filter noisy hypernyms database.

Induced Senses with Hypernymy Labels

ID: Word Sense, $s \in \mathcal{S}$	**Local Sense Cluster: Related Senses, $\mathcal{N}(s) \subset \mathcal{S}$**	**Hypernyms, $\mathcal{H}(s) \subset \mathcal{S}$**
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, …

Table: Induced senses representing "fruits" and "programming language".

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.

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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:

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

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

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

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

Induced Global Semantic Classes

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 semantic classes representing "fruits" and "programming language" semantic classes.

Labelling of the Induced Semantic Classes

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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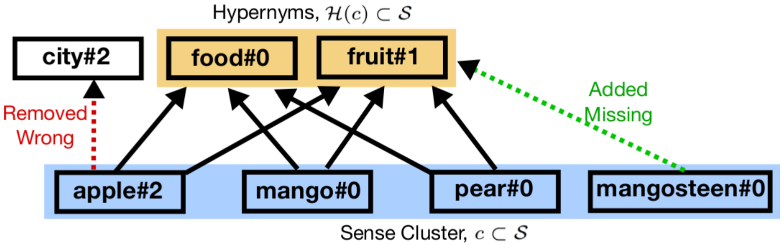
Denoising Hypernyms using the Distributional Semantic Classes

- 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.

An Illustration of Hypernymy Extraction and Correction



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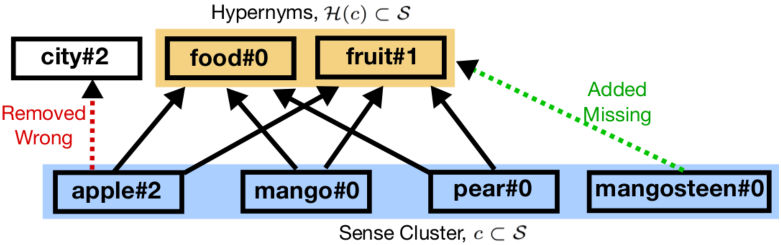

- Post-processing of hypernymy relations using distributionally induced semantic classes, represented by clusters of induced word senses labeled with noisy hypernyms.

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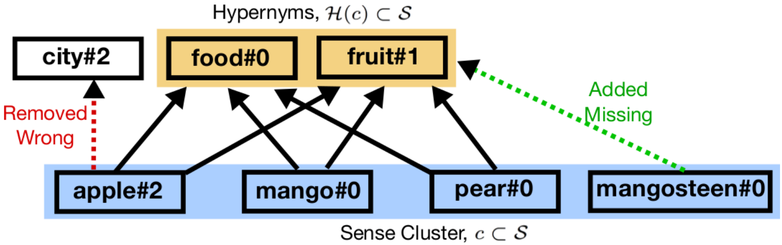

- Post-processing of hypernymy relations using distributionally induced semantic classes, represented by clusters of induced word senses labeled with noisy hypernyms.
- Wrong hypernyms outside the cluster labels are removed, while the missing ones not present in the noisy database of hypernyms are added.

Outline

Taxonomy Enrichment using Hyperbolic Embeddings

- Based on publication [5].

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  - **Adding absent** edges: $E = E \cup \{E_{abs}\}$ and
  - **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

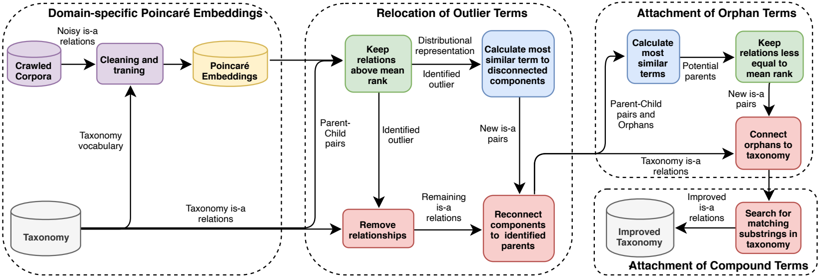

Figure: Outline of the taxonomy refinement method.

Taxonomy Enrichment using Hyperbolic Embeddings

Two types of hypernym-hyponym distance measures

- **Co-hyponyms**: Distance between two terms $\mathbf{u}, \mathbf{v} \in \mathbb{R}^d$ in Euclidean space:

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- **Hypernyms**: Distance between two terms $\mathbf{u}, \mathbf{v} \in \mathcal{B}^d$ for a d-dimensional Poincaré Ball model:

$$d(\mathbf{u}, \mathbf{v}) = \operatorname{arcosh}\left(1 + 2\frac{||\mathbf{u} - \mathbf{v}||^2}{(1 - ||\mathbf{u}||^2)(1 - ||\mathbf{v}||^2)}\right).$$

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

Taxonomy Enrichment using Hyperbolic Embeddings

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5. Compute distance to the closest co-hyponym for every node to identify and relocate outliers.

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1. Attach orphans by computing the rank between every orphan and the most similar node in the taxonomy.

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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

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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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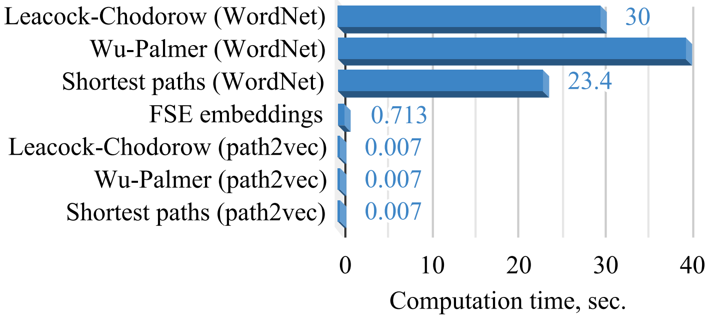

Figure: Similarity computation: graph vs vectors.

Node Embeddings of Lexical-Semantic Graphs

Computing Training Similarities

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- Such pruning does not lead to loss of effectiveness.

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- Examples:
  - "We were not able to travel in the weather, and there was no **phone**." $\rightarrow$ **telephone**

Lexical Substitution and Analysis of Semantic Relations

- Given a sentence S composed of a context C and a target word T find **lexical substitutes**: words/phrases which can be used to replace T without changing meaning of S.
- Examples:
  - "We were not able to travel in the weather, and there was no **phone**." $\rightarrow$ **telephone**
  - "What happened to the big, new garbage **can** at Church and Chambers Streets?" $\rightarrow$ **bin**, **disposal**, **container**

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.

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

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

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

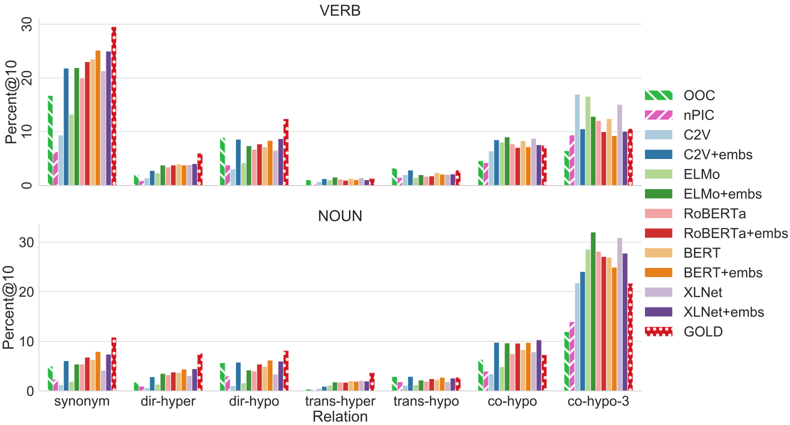

Figure: Proportions of substitutes related to the target by various semantic relations according to WordNet.

Outline

Summary

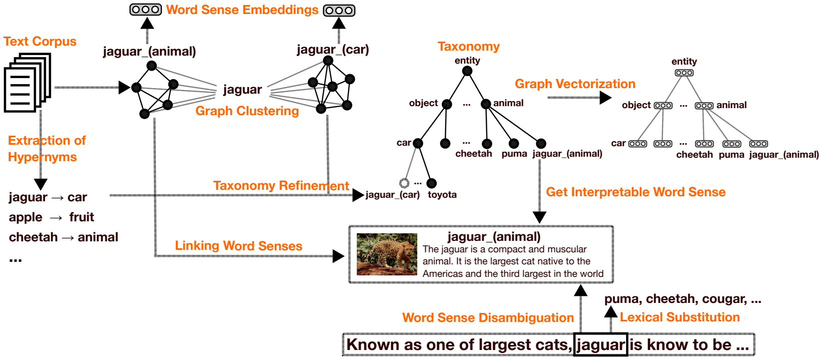

Figure: Overview of various methods for computational lexical semantics presented in this dissertation and their interrelations.

Thank you

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- ACL-2024 Shared Task on **Knowledge Graph Question Answering (KGQA)**: `https://sites.google.com/view/textgraphs2024/home/shared-task`
- CLEF-2024 Shared Task on **Multilingual Text Detoxification**: `http://pan.webis.de/clef24/pan24-web/text-detoxification.html`
- **Master program on Data Science / AI at Skoltech**: `https://msc.skoltech.ru`. Deadlines: 11.03, 27.05, 15.08.
- Forthcoming paper at COLING-LREC 2024:

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