Methods and Algorithms for Extraction, Linking, Vectorisation, and Disambiguation of Lexical-Semantic Graphs

Alexander Panchenko
Skolkovo Institute of Science and Technology and
Artificial Intelligence Research Institute

18.12.2024

Outline

Dissertation

Национальный исследовательский университет «Высшая школа экономики» → Диссертации → Методы и алгоритмы для извлечения, связывания, векторизации и разрешения неоднозначности лексико-семантических графов

Методы и алгоритмы для извлечения, связывания, векторизации и разрешения неоднозначности лексико-семантических графов

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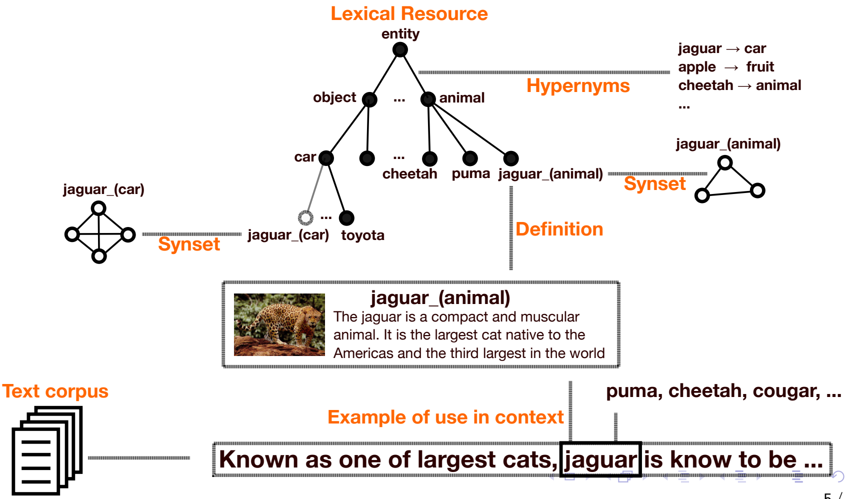
- `https://AlexanderPanchenko.github.io`
- `https://www.hse.ru/sci/diss/933095100`

Outline

Object: Lexical-semantic graphs i.e. word senses connected with semantic relations, e.g. synonyms and hypernyms



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- **precise** and **interpretable** manually created lexical-semantic graphs with **low coverage**, e.g.:
  - taxonomies,
  - WordNets,
  - ...

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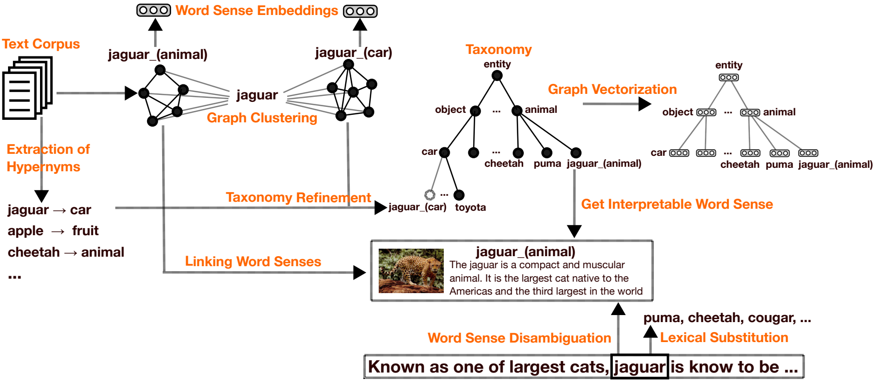
- **precise** and **interpretable** manually created lexical-semantic graphs with **low coverage**, e.g.:
  - taxonomies,
  - WordNets,
  - ...
- **noisy** and **non-interpretable** automatically induced from text distributional lexical representations with **high coverage**, e.g.:
  - distributional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

Proposed methods and their interrelations



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3. **linking** word senses of manually and automatically created lexical-semantic graphs,
4. **disambiguation** in context with respect to the induced sense representations,
5. **vectorization** of lexical semantic-graphs for the use in various applications.

History of research behind this dissertation

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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.

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), (Portorož, 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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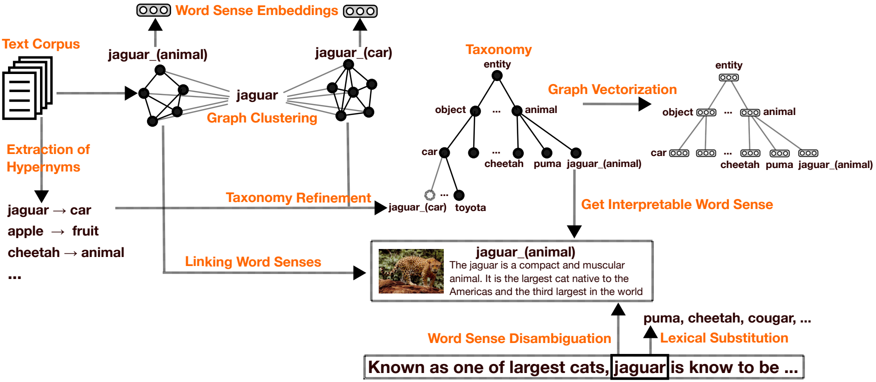
Proposed methods and their interrelations



Graph Clustering

Task Definition:

- 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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- We denote a subset of nodes $C^i \subseteq V$ as a **cluster**.
- A **graph clustering** is a function $\textsc{Cluster} : (V, E) \to C$ such that $V = \bigcup\limits_{C^i \in C} C^i$.
- 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

- Based on publications [6, 9, 10]: COLI, ACL, ACL.

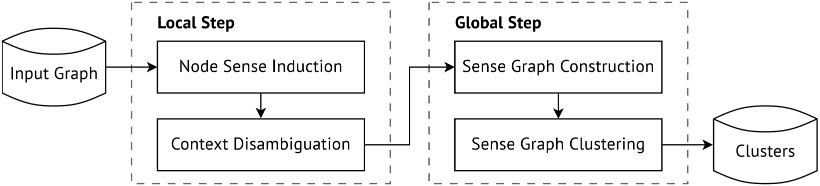
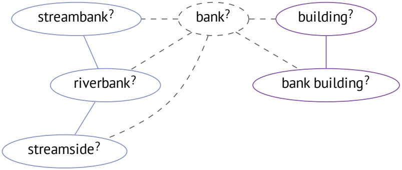


Figure: The outline of the algorithm showing the *local* step of node sense induction and context disambiguation, and the *global* step of sense graph constructing and clustering.

Local Step: Disambiguation of Ego-Networks



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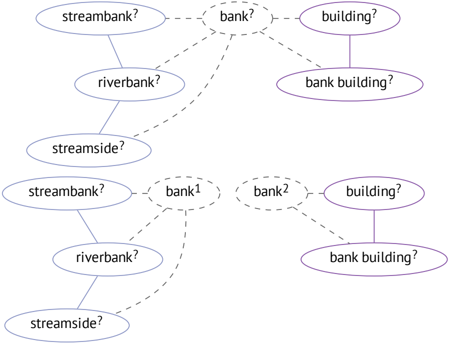

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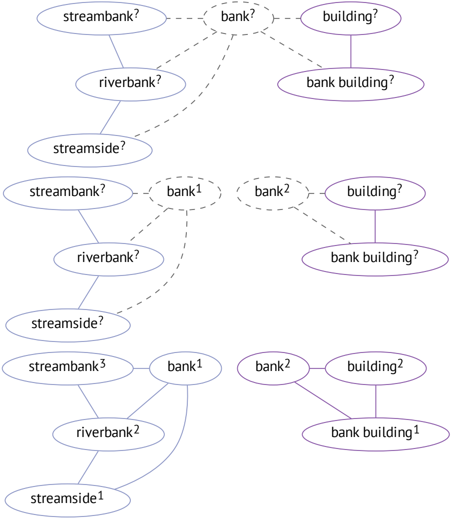
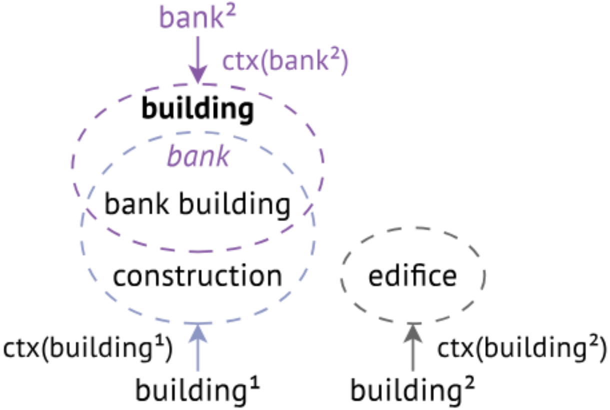


Matching the meaning of the ambiguous node "building" in the context of the sense bank^2



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 $\mathrm{sim} : (\mathrm{ctx}(a), \mathrm{ctx}(b)) \to \mathbb{R}, \forall\, \mathrm{ctx}(a), \mathrm{ctx}(b) \subseteq V$.
Output: clusters C.

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for all $u \in V$ **do** ▷ Local Step: Sense Induction
  $\mathrm{senses}(u) \leftarrow \emptyset$
  $V_u \leftarrow \{v \in V : \{u, v\} \in E\}$ ▷ Note that $u \notin V_u$
  $E_u \leftarrow \{\{v, w\} \in E : v, w \in V_u\}$
  $G_u \leftarrow (V_u, E_u)$
  $C_u \leftarrow \mathrm{Cluster}_{\mathsf{Local}}(G_u)$ ▷ Cluster the open neighborhood of u
  for all $C_u^i \in C_u$ **do**
    $\mathrm{ctx}(u^i) \leftarrow C_u^i$
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$\mathcal{V} \leftarrow \bigcup_{u \in V} \mathrm{senses}(u)$ ▷ Global Step: Sense Graph Nodes
for all $\hat{u} \in \mathcal{V}$ **do** ▷ Local Step: Context Disambiguation
  $\widehat{\mathrm{ctx}}(\hat{u}) \leftarrow \emptyset$
  for all $v \in \mathrm{ctx}(\hat{u})$ **do**
    $\hat{v} \leftarrow \arg\max_{v' \in \mathrm{senses}(v)} \mathrm{sim}(\mathrm{ctx}(\hat{u}) \cup \{u\}, \mathrm{ctx}(v'))$ ▷ $\hat{u}$ is a sense of $u \in V$
    $\widehat{\mathrm{ctx}}(\hat{u}) \leftarrow \widehat{\mathrm{ctx}}(\hat{u}) \cup \{\hat{v}\}$
$\mathcal{E} \leftarrow \{\{\hat{u}, \hat{v}\} \in \mathcal{V}^2 : \hat{v} \in \widehat{\mathrm{ctx}}(\hat{u})\}$ ▷ Global Step: Sense Graph Edges
$\mathcal{G} \leftarrow (\mathcal{V}, \mathcal{E})$ ▷ Global Step: Sense Graph Construction

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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

Synsets extracted from graph of synonyms

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

Semantic frames

Example of a tricluster of lexical units corresponding to the "Kidnapping" frame from FrameNet.

FrameNet	Role	Lexical Units (LU)
Perpetrator	Subject	kidnapper, alien, militant
FEE	Verb	snatch, kidnap, abduct
Victim	Object	son, people, soldier, child

Semantic frames extracted from graph of SVO triples

# 1268	**Subjects:**	expert, scientist, lecturer, engineer, analyst
	Verbs:	study, examine, tell, detect, investigate, do, observe, hold, find, have, predict, claim, notice, give, discover, explore, learn, monitor, check, recognize, demand, look, call, engage, spot, inspect, ask
	Objects:	view, problem, gas, area, change, market
# 1378	**Subjects:**	leader, officer, khan, president, government, member, minister, chief, chairman
	Verbs:	belong, run, head, spearhead, lead
	Objects:	party, people
# 4211	**Subjects:**	evidence, research, report, survey
	Verbs:	prove, reveal, tell, show, suggest, confirm, indicate, demonstrate
	Objects:	method, evidence

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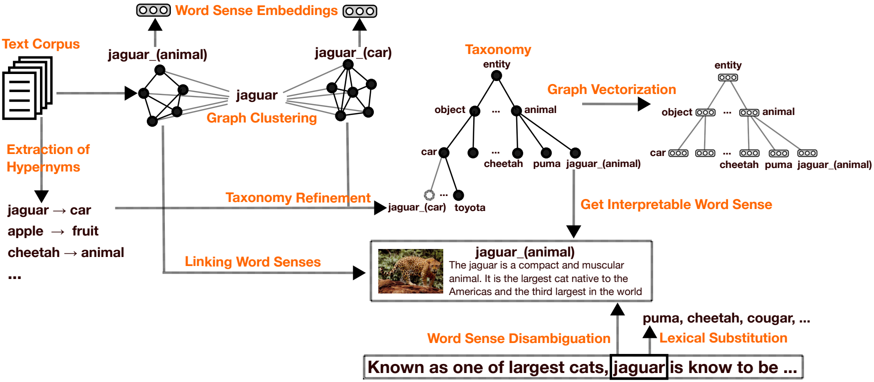
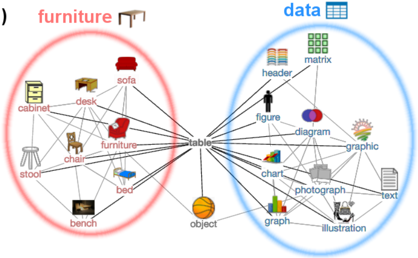


Making induced senses human-interpretable

- Based on publications [1] and [18]: EACL and EMNLP.
- Levels of interpretability:
  1. word sense inventory;
  2. sense feature representation;
  3. results of disambiguation in context.

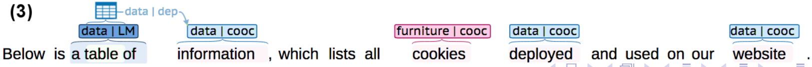
(1)



(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)



Knowledge-based sense representations are interpretable

Making induced senses interpretable for humans

Sentence

Jaguar is a large spotted predator of tropical America similar to the leopard.

Word

Jaguar

Model

Word Senses based on Cluster Word Features

PREDICT SENSE | RANDOM SAMPLE

Predicted senses for 'Jaguar'

1. jaguar (animal)

Similarity score: 0.00184 / Confidence: 99.87% / Sense ID: jaguar#0 / BabelNet ID: bn:00033987n

Hypernyms: animal, wildlife, bird, mammal

Sample sentences:

The **jaguar**, a compact and well-muscled animal, is the largest cat in the New World.

Jaguar may leap onto the back of the prey and sever the cervical vertebrae, immobilizing the target.

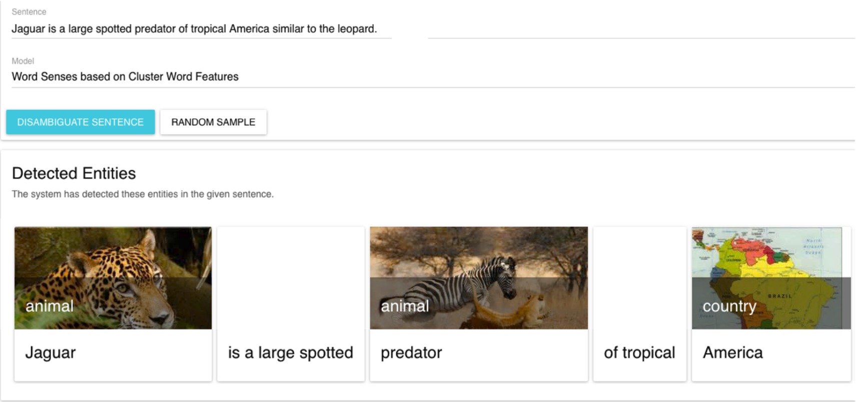
Cluster words: lion, tiger, leopard, wolf, monkey, otter, crocodile, alligator, deer, cat, elephant, fox, eagle, owl, snake

Context words: elephant: 0.012, tiger: 0.012, fox: 0.0099, wolf: 0.0097, cub: 0.0086, monkey: 0.0083, leopard: 0.0074, eagle: 0.0062, den: 0.0043, elk: 0.0040, 32078 more not shown

Matching features: leopard: 0.0011, predator: 0.00040, spotted: 0.00038, large: 0.0000041, similar: 0.0000015, tropical: 5.6e-7, america: 2.0e-7

BABELNET LINK | SHOW LESS

Making induced senses interpretable for humans



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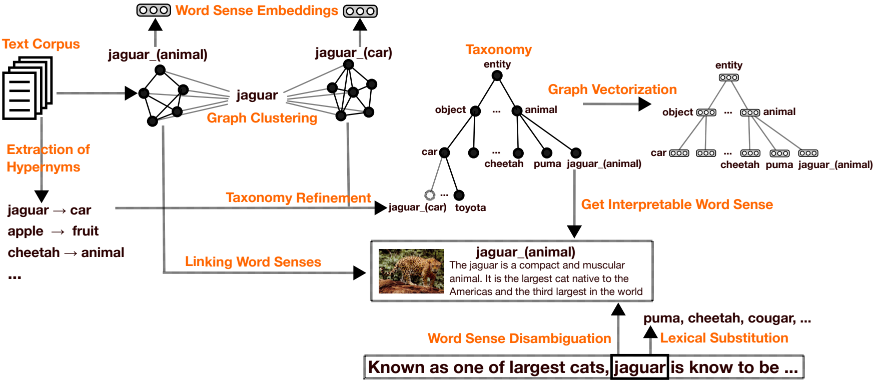

Linking Word Sense Representations

- Based on publications [7, 8]: ISWC and NLE.

Task Definition: Sense Linking

Input:

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

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- **PCZ** $T = \{(j_i, R_{j_i}, H_{j_i})\}$, where
  - 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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- **LR** W: lexical resource, e.g. WordNet or BabelNet;
- **PCZ** $T = \{(j_i, R_{j_i}, H_{j_i})\}$, where
  - j_i is a sense identifier, i.e. mouse:1,
  - R_{j_i} the set of its semantically related senses, i.e. $R_{j_i} = \{\text{keyboard:1, computer:0, } \dots\}$,
  - H_{j_i} the set of its hypernym senses, i.e. $\{\text{equipment:3}, \dots\}$.

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

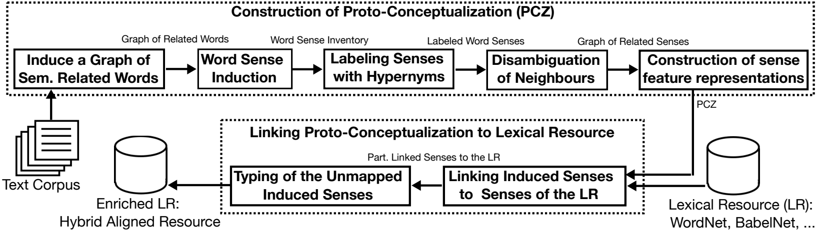

Figure: A distributional semantic model is used to construct a disambiguated distributional lexical semantic network (a proto-conceptualization, PCZ), which is subsequently linked to the lexical resource (LR).

Linking Word Sense Representations

Input: $T = \{(j_i, R_{j_i}, H_{j_i})\}, W, th, m$
Output: $M = (source, target)$
$M = \emptyset$

Linking Word Sense Representations

Input: $T = \{(j_i, R_{j_i}, H_{j_i})\}$, W, th, m
Output: $M = (source, target)$

$M = \emptyset$
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**
      $M = M \cup \{(j_i, c_0)\}$

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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**
      $rank(c_k) = sim(j_i, c_k, M)$

Linking Word Sense Representations

Input: $T = \{(j_i, R_{j_i}, H_{j_i})\}$, W, th, m
Output: $M = (source, target)$

```
M = ∅
for all (j_i, R_{j_i}, H_{j_i}) ∈ 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, ∅) ≥ th then
            M = M ∪ {(j_i, c_0)}
for step = 1; step ≤ m ; step = step + 1 do
    M_step = ∅
    for all (j_i, R_{j_i}, H_{j_i}) ∈ T.senses / M.senses do
        C(j_i) = W.getSenses(j_i.lemma, j_i.POS)
        for all c_k ∈ 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
            if rank(c_t) ≥ th then
                M_step = M_step ∪ {(j_i, c_t)}
    M = M ∪ M_step
```

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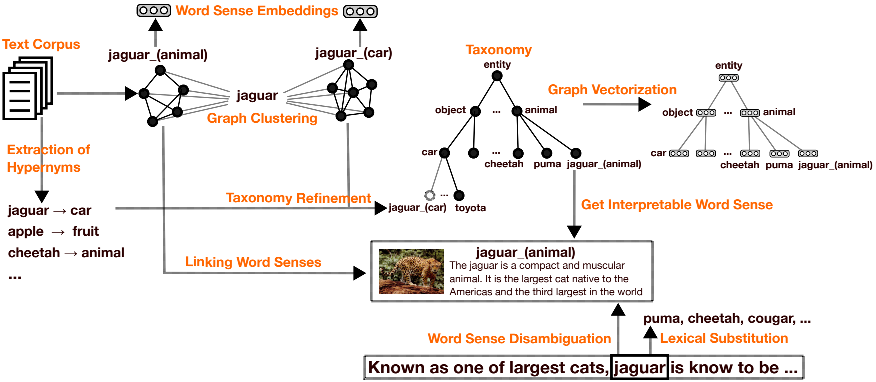
  $M = M \cup M_{step}$
for all $(j_i, R_{j_i}, H_{j_i}) \in T.senses/M.senses$ **do**
  $M = M \cup \{(j_i, j_i)\}$
return M

Example of Linked Word Sense Representations

WordNet ID	PCZ ID	PCZ Related Terms	PCZ Context Clues
mouse:n:1	mouse:0	rat:0, rodent:0, monkey:0, ...	rat:conj_and, gray:amod, ...
mouse:n:4	mouse:1	keyboard:1, computer:0, printer:0 ...	click:-prep_of, click:-nn, ...
keyboard:n:1	keyboard:0	piano:1, synthesizer:2, organ:0 ...	play:-dobj, electric:amod, ..
keyboard:n:1	keyboard:1	keypad:0, mouse:1, screen:1 ...	computer, qwerty:amod ...

Outline

Proposed methods and their interrelations



Word Sense Embeddings

- Based on publications [17, 20]: ReprLearn @ ACL and LREC.

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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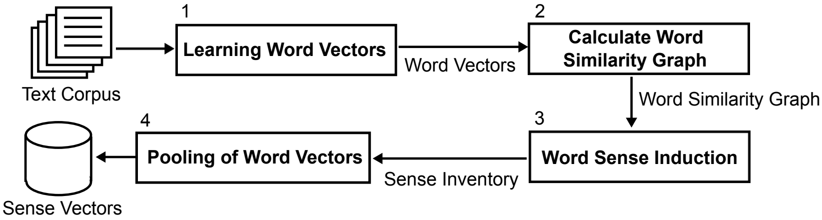
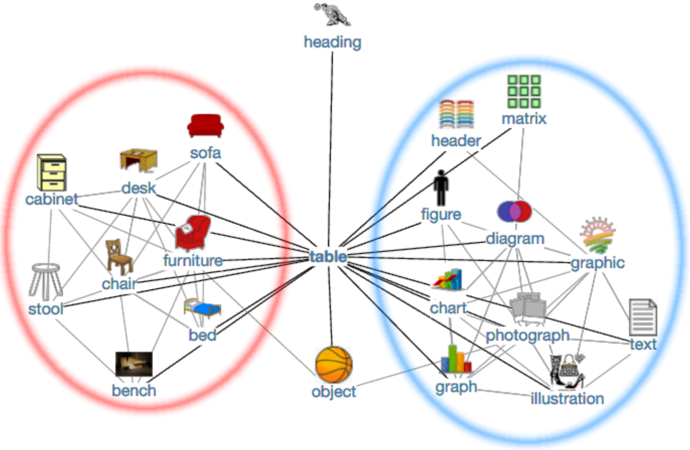
Task formulation

- **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.
- **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



Standard ego-network from distributionally similar words



Graph-based Word Sense Induction (WSI)

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
    V ← N most similar terms of t from T
    G ← graph with V as nodes and no edges E
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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

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        end
    end
    $S_t \leftarrow \texttt{ChineseWhispers}(G)$
    $S_t \leftarrow \{s \in S_t : |s| \geq k\}$
end

Vector arithmetic for sense induction

1. **Get the neighbors** of a target word, e.g. **"bank"**:
   1. lender
   2. river
   3. citybank
   4. slope
   5. ...
2. Get **similar to "bank"** and **dissimilar to "lender"**:
   1. river
   2. slope
   3. land
   4. ...
3. **Compute distances** to **"lender"** and **"river"**.

Graph-vector sense induction

1. **For** i-th neighbor of the target word w among k neighbors:
    1. Get a pair of opposite words for the w_i neighbor: (w_j, w_k)
        - For each w_i a (node, **anti-node**) pair is computed
        - For each w_i compute $\delta_i = \mathbf{w} - \mathbf{w}_i$.
        - Anti-node is most similar neighbor of w to δ_i
    2. Add them as nodes: $V = V \cup \{w_j, w_k\}$
    3. Remember the pair as an **anti-edge**: $A = A \cup (w_j, w_k)$

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4. **Find cluster labels** by finding the central nodes in a cluster.

Graph-vector sense induction

- **Get the neighbors** of a target word, e.g. **"java"**:
  1. Python
  2. Borneo
  3. C++
  4. Sumatra
  5. Arabica
  6. Robusta
  7. Ruby
  8. JavaScript
  9. Bali
  10. ...

Graph-vector sense induction

- **Get the neighbors** of a target word, e.g. **“java”**:
  1. Python $\neq$ Borneo
  2. Borneo $\neq$ Scala
  3. C++ $\neq$ Borneo
  4. Sumatra $\neq$ highway
  5. Arabica $\neq$ Python
  6. Robusta $\neq$ Python
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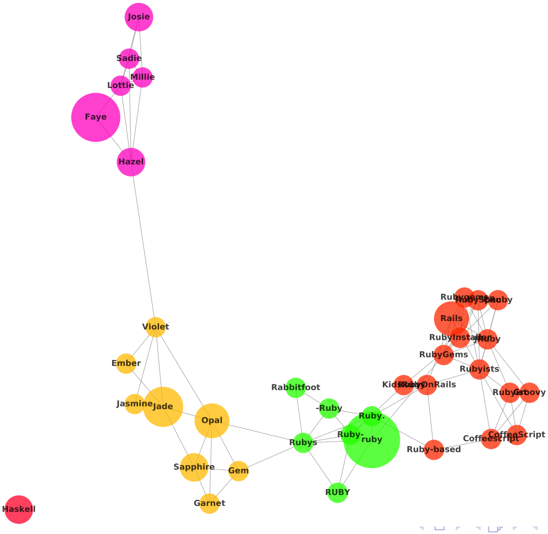
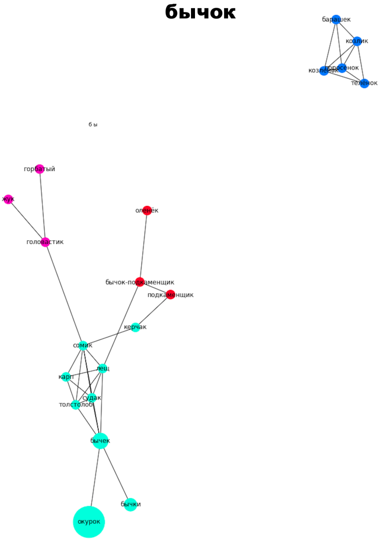
- **Nodes**:
  1. Python
  2. Borneo
  3. C++
  4. Arabica
  5. Robusta
  6. Ruby

Sense induction example (Ruby)



Sense induction example



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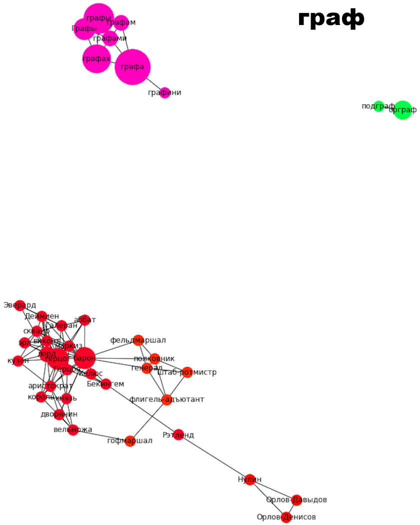

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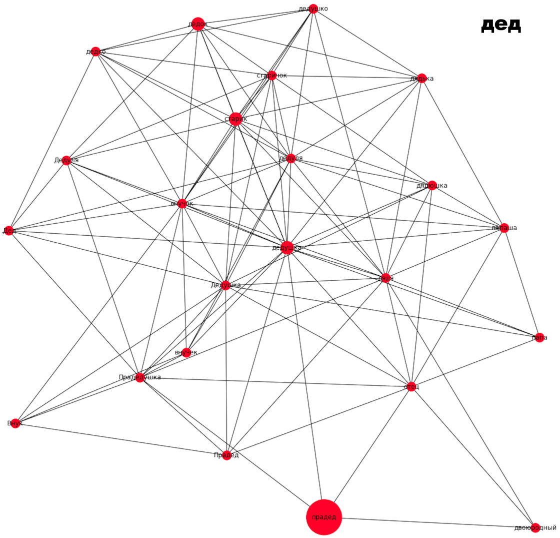

Word Sense Embeddings

- **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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- **Word Sense Disambiguation**:
  $$s^* = \arg\max_i sim(\mathbf{s}_i, C) = \arg\max_i \frac{\bar{\mathbf{c}}_w \cdot \mathbf{s}_i}{\|\bar{\mathbf{c}}_w\| \cdot \|\mathbf{s}_i\|},$$
  where $\bar{\mathbf{c}}_w = k^{-1} \sum_{i=1}^{k} vec_w(c_i)$.

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  where $\bar{\mathbf{c}}_w = k^{-1} \sum_{i=1}^{k} vec_w(c_i)$.
- **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.

Sense embeddings using retrofitting

- Neighbours of Word and Sense Vectors

Vector	**Nearest Neighbors**
table	tray, bottom, diagram, bucket, brackets, stack, basket, list, parenthesis, cup, saucer, pile, playfield, bracket, pot, drop-down, cue, plate

Sense embeddings using retrofitting

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Vector	Nearest Neighbors
table	tray, bottom, diagram, bucket, brackets, stack, basket, list, parenthesis, cup, saucer, pile, playfield, bracket, pot, drop-down, cue, plate
table#0	leftmost#0, column#1, tableau#1, 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, pan#1, lid#0

Keywords and sense clusters for words “mouse” and “apple”

Label	**Nearest neighbours**
	MOUSE
computer mouse types	touch-pad, logitec, scrollwheel, **mouses**, mouse.It, mouse.The, joystick, trackpads, nano-receiver, 800DPI, nony, track-pad, M325, keyboard-controlled, Intellipoint, MouseI, intellimouse, Swiftpoint, Evoluent, 800dpi, moused, game-pad, steelseries, ErgoMotion, IntelliMouse, <...>
computer mouse actions	Ctrl-Alt, right-mouse, cursor, left-clicks, spacebar, rnUse, mouseclick, **click**, mousepointer, keystroke, cusor, mousewheel, MouseMove, mousebutton, leftclick, click-dragging, mouse-button, cursor., arrow-key, double-clicks, mouse-down, ungrab, mouseX, arrow-keys, right-button, <...>
rodent	Rodent, rodent, mousehole, rats, **mice**, mice-, hamster, SOD1G93A, meeses, mice.The, PDAPP, hedgehog, Maukie, rTg4510, mousey, meeces, rodents, cat, White-footed, rat, Mice, <...>
keyboard	keyborad, keybard, keybord, keyboardThe, keyboad, keyboar, **Keyboard**, keboard, keyboardI, keyb, key-board.This, keybaord, keyboard
medical	SENCAR, mTERT, **mouse-specific**
Latin	Apodemus, **Micormys**
Latin	**Akodon**
	APPLE
iphone	mobileme, idevice, carplay, iphones, icloud, iwatch, ios5, ipod, **iphone**, android, ifans, iphone.I, iphone4, iphone5s, idevices, ipad, ios, ipad., iphone5, iphone., ios7
fruit	**apples**, apple-producing, Honeycrisp, apple-y, Macouns, apple-growing, pear, apple-pear, Gravensteins, apple-like, Apples, Honeycrisps, apple-related, Borkh, Braeburns, Starkrimson, Apples-, SweeTango, Elstar
macbook	macbook, macbookpro, macbookair, imac, ibooks, **tuaw**, osx, macintosh, imacs, apple.com, applestore, Tagsap-ple, stevejobs, applecare
fruit, typos pinklady	blackerry, blackberry, blueberry, aplle, cidar, **apple.The**, apple.I, aple, appple, calvados, pie.It,
tokenisation issues, typos	Apple.This, AMApple, it.Apple, too.Apple, AppleApple, **up.Apple**, AppleA, Aplle, Apple.Apple
Apple criticism	anti-apple, Aple, Crapple, isheep, iDiots, crapple, Appple, iCrap, **non-apple**
Bible	**Adam**
cooking	**caramel-dipped**
iphone	**earpod**

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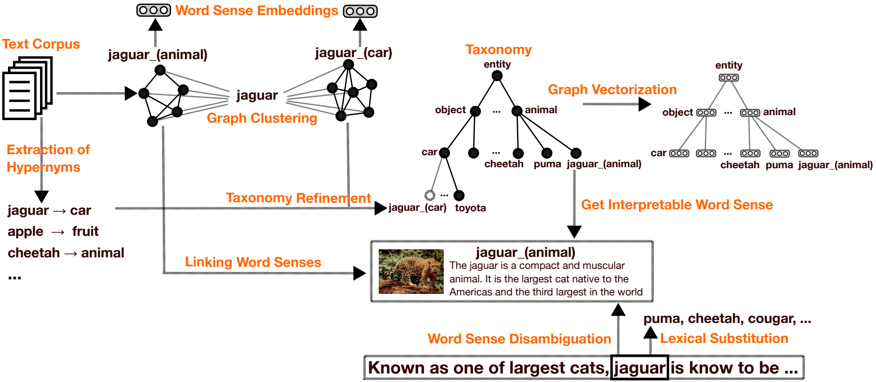

Graph-based similarity measures

- Based on publication [3]: ACL.

Introduction

- **Graph node similarity measures** $sim : V \times V \to \mathbb{R}$ on pairs of nodes V of a graph $G = (V, E)$:
  - travel time,
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- Computing directly on the graph can be prohibitively computationally expensive.

Node Embeddings of Lexical-Semantic Graphs

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

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

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- α is a regularization coefficient.

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- **Leackock-Chodorow**: $sim_(w_i, w_j) = \frac{\text{depth}(\text{lcs}(w_i, w_j)}{\text{depth}(w_i) + \text{depth}(w_j)}$,
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- **Wu-Palmer**: $sim_(w_i, w_j) = -\log \text{pathlen}(w_i, w_j)$.

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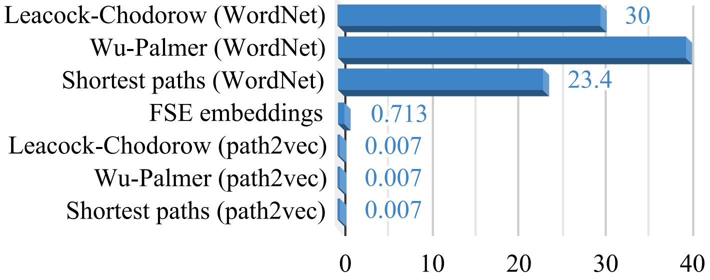
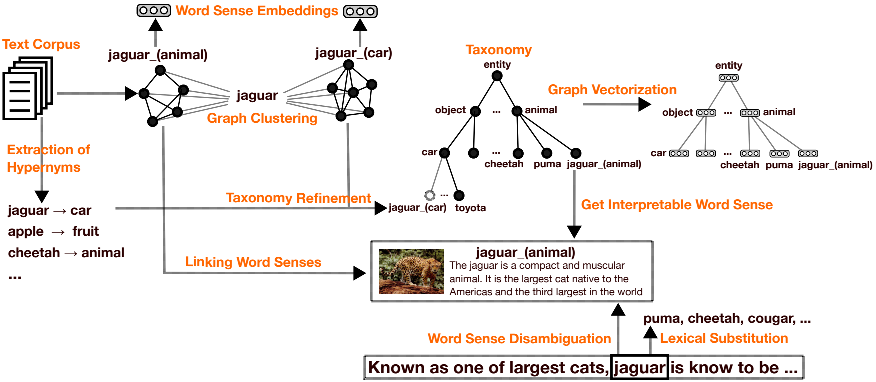
- **Wu-Palmer**: $sim_{(}w_i, w_j) = -\log \text{pathlen}(w_i, w_j)$.



- Tested on WordNet, DBpedia, and Freebase graphs.

Outline

Proposed methods and their interrelations



Prediction of Hypernym Embeddings

- **Hypernymy** represent hierarchical relations between terms:
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Hypernymy Extraction via **regularized** Projection Learning

- **Asymmetric Regularization.** Enforces the asymmetry:

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

- **Neighbor Regularization.** Semantically related words $\vec{z}$:

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Extracting of Hypernyms via Sense Graph Clustering

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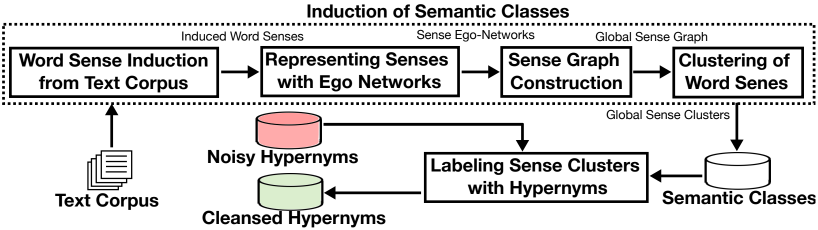

Figure: Sense-aware distributional semantic classes are induced from a text corpus and then used to filter noisy hypernyms database.

Extracting of Hypernyms via Sense Graph Clustering

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

Extracting of Hypernyms via Sense Graph Clustering

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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

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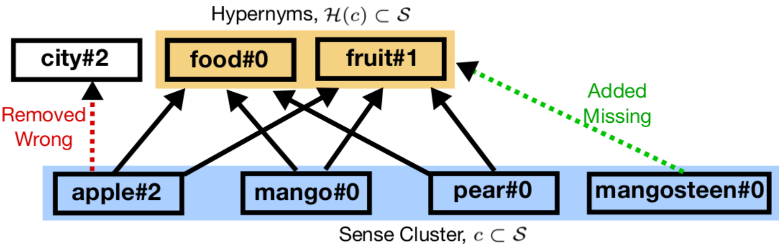
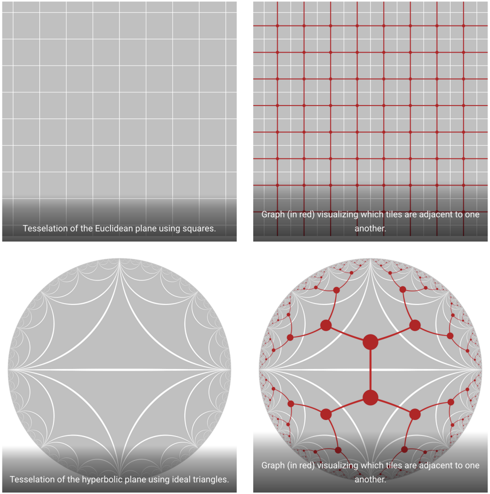


Euclidian vs Hyperbolic Geometry



Tesselation of the Euclidean plane using squares.

Graph (in red) visualizing which tiles are adjacent to one another.

Tesselation of the hyperbolic plane using ideal triangles.

Graph (in red) visualizing which tiles are adjacent to one another.

Image source: `https://www.h-its.org/projects/`

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:

$$d(\mathbf{u}, \mathbf{v}) = 1 - \frac{\mathbf{u} \cdot \mathbf{v}}{|\mathbf{u}||\mathbf{v}|},$$

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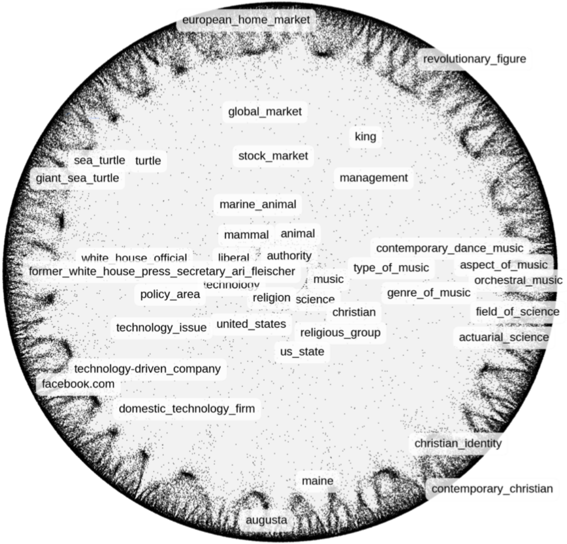
- **Hypernyms**: Distance between two terms $\mathbf{u}, \mathbf{v} \in \mathcal{B}^d$ for a d-dimensional Poincaré Ball model:

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

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

Taxonomy Enrichment using Hyperbolic Embeddings



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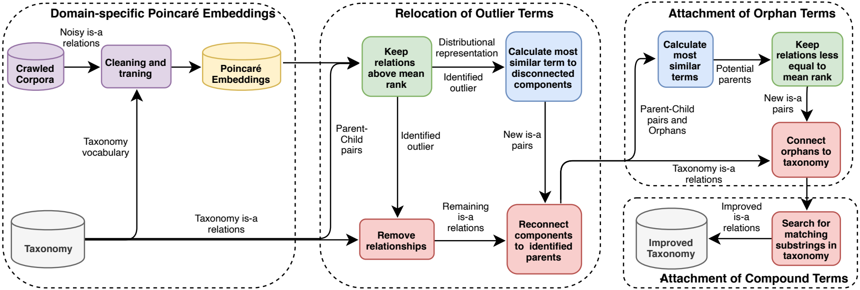

Figure: Outline of the taxonomy refinement method.

Outline

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Summary of the obtained results (cont'd)

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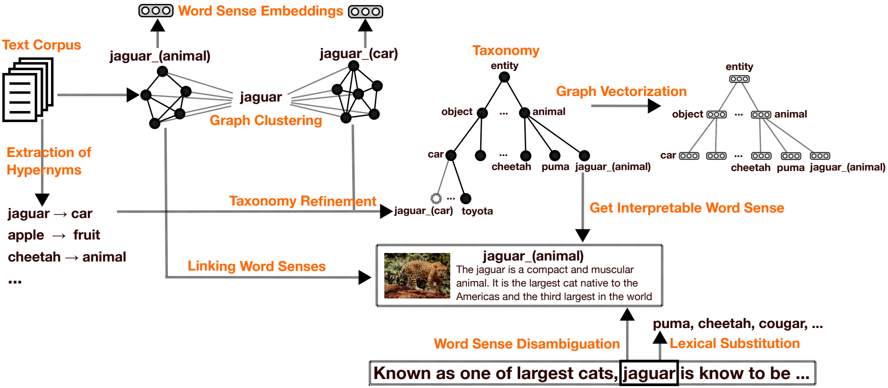

Figure: Overview of various methods for computational lexical semantics presented in this dissertation and their interrelations.

Acknowledgements

- **Christian Biemann** as the main advisor and supporter.
- Key co-authors: **Dmitry Ustalov**, **Nikolay Arefyev**, **Simono Paolo Ponzetto**, **Stefano Faralli**, and **Andrey Kutuzov**.
- Key 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, guided and encouraged during the manuscript preparation: Elena Gryazina and Elena Tutubalina.
- My family: Luidmila Borisovna, Ivan Ivanovich, Polina, Evgenii, Konstantin, and Ivan.

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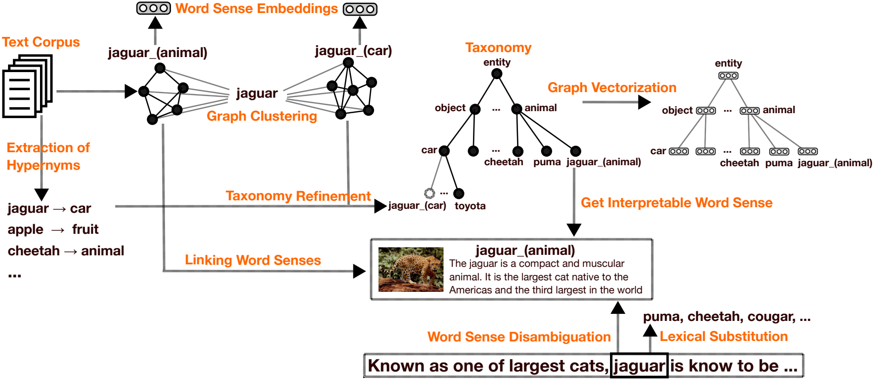
Proposed methods and their interrelations



Prediction of Hypernym Embeddings

- Based on publications [4].

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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:

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

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Performance of our approach for Russian for $k = 20$ clusters compared to Fu et al. [43].

Model		**hit@1**	**hit@5**	**hit@10**	**AUC**
Baseline		0.209	0.303	0.323	2.665
Asym. Reg.	$\vec{x}\mathbf{\Phi}$	0.213	0.300	0.322	2.659
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Neig. Reg.	$\vec{x}\mathbf{\Phi}$	**0.214**	0.304	0.325	2.685
Neig. Reg.	$\vec{x}\mathbf{\Phi}\mathbf{\Phi}$	0.211	**0.315**	**0.338**	**2.768**

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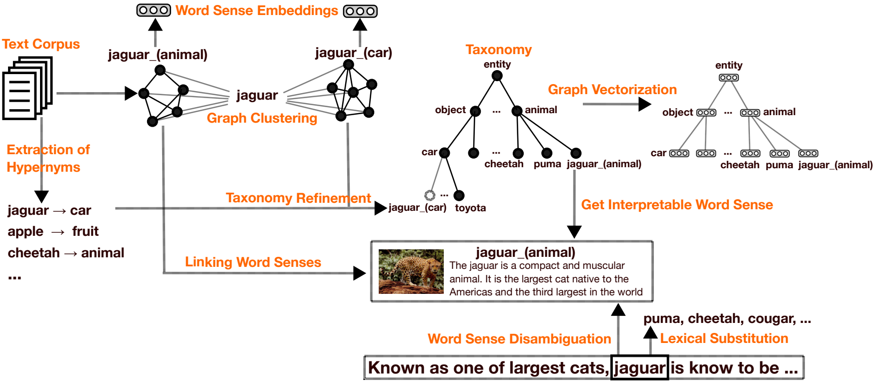

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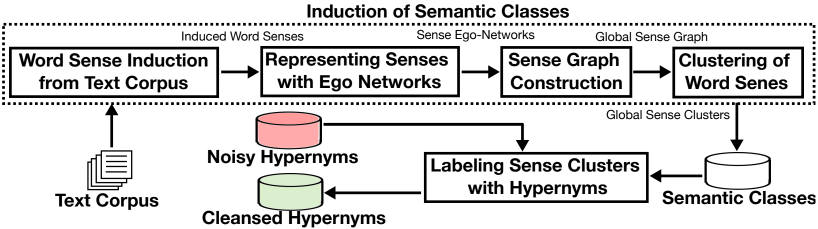

Figure: Sense-aware distributional semantic classes are induced from a text corpus and then used to filter noisy hypernyms database.

Induced Senses with Hypernymy Labels

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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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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:

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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

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Labelling of the Induced Semantic Classes

Clustering of Word Senses

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

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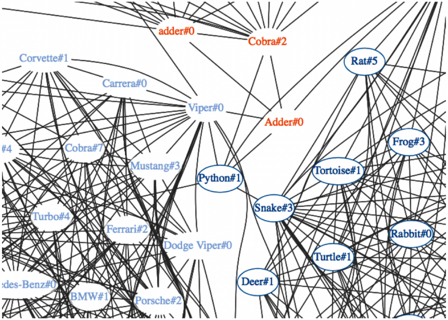
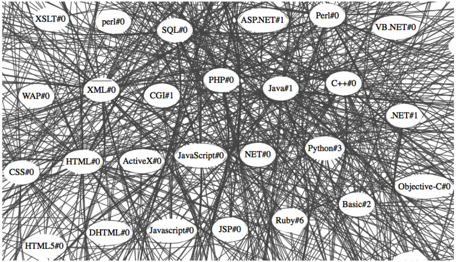
- Sense cluster is labeled with top 5 common hypernyms.
- For labeling we used the tf–idf weighting:

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

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


adder#0
Cobra#2
Corvette#1
Rat#5
Carrera#0
Viper#0
Adder#0
Frog#3
Cobra#7
Mustang#3
Tortoise#1
Python#1
Snake#3
Turbo#4
Ferrari#2
Rabbit#0
Dodge Viper#0
Turtle#1
Deer#1
BMW#1
Porsche#2


XSLT#0
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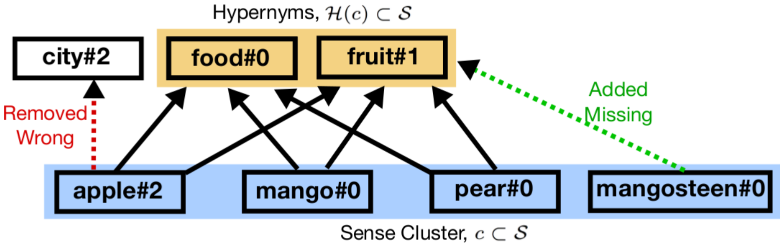
SQL#0
ASP.NET#1
Perl#0
VB.NET#0
PHP#0
Java#1
C++#0
WAP#0
XML#0
CGI#1
.NET#1
Python#3
JavaScript#0
NET#0
HTML#0
ActiveX#0
CSS#0
Objective-C#0
Basic#2
Ruby#6
DHTML#0
Javascript#0
JSP#0
HTML5#0

An Illustration of Hypernymy Extraction and Correction



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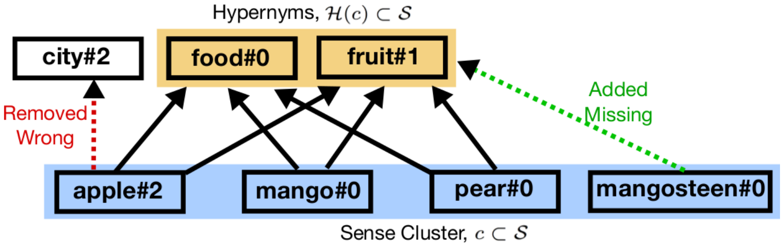

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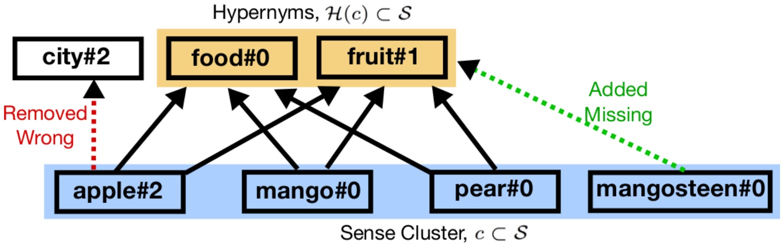
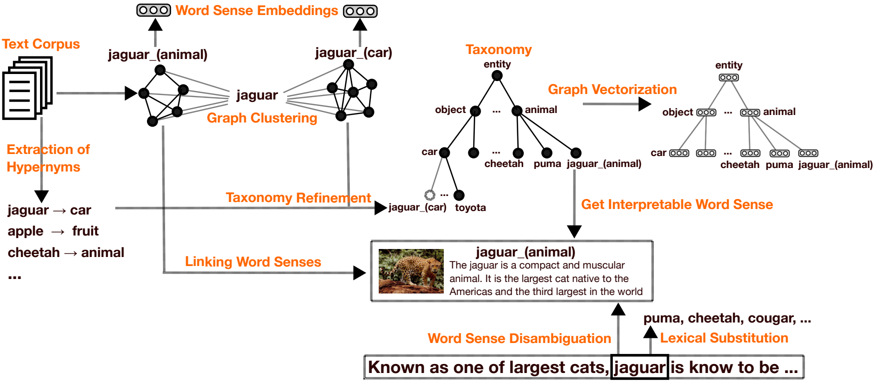


- Post-processing of hypernymy relations using distributionally induced semantic classes, represented by clusters of induced word senses labeled with noisy hypernyms.
- Wrong hypernyms outside the cluster labels are removed, while the missing ones not present in the noisy database of hypernyms are added.

Outline

Proposed methods and their interrelations



Taxonomy Enrichment using Hyperbolic Embeddings

- Based on publication [5].

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  - 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

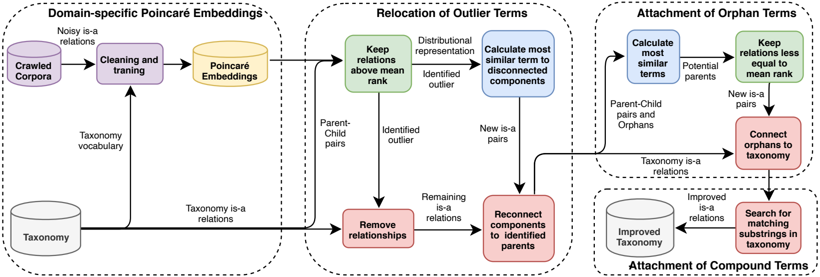

Figure: Outline of the taxonomy refinement method.

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:

$$d(\mathbf{u}, \mathbf{v}) = 1 - \frac{\mathbf{u} \cdot \mathbf{v}}{|\mathbf{u}||\mathbf{v}|},$$

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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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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.

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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.

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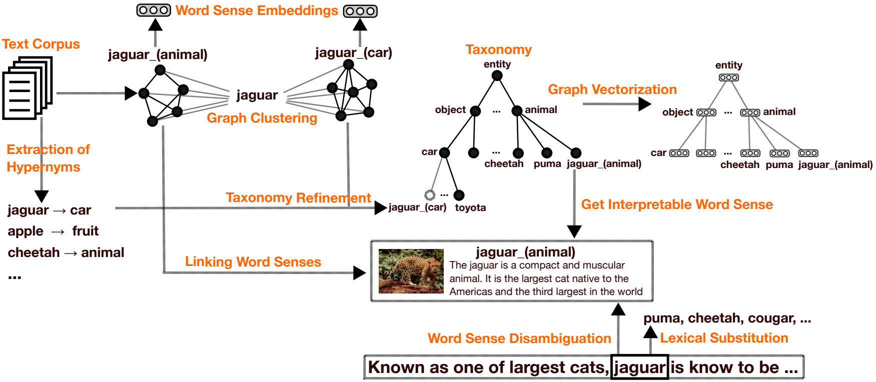

Lexical Substitution and Analysis of Semantic Relations

- 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.

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- 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**

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

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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

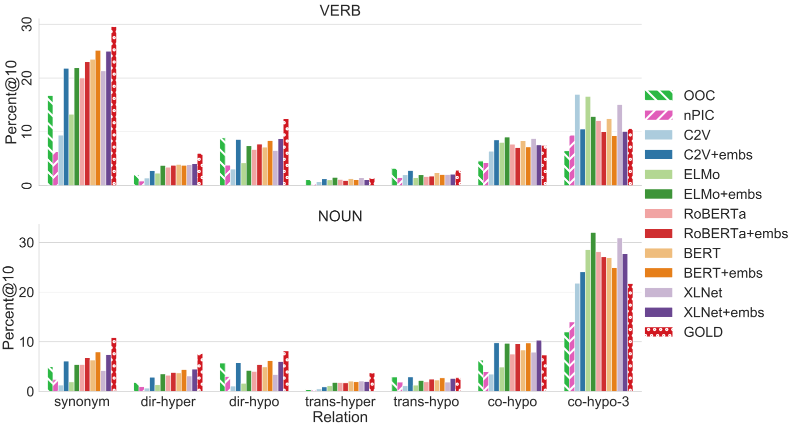

Figure: Proportions of substitutes related to the target by various semantic relations according to WordNet.

A. Panchenko, E. Ruppert, S. Faralli, S. P. Ponzetto, and C. Biemann, "**Unsupervised does not mean uninterpretable: The case for word sense induction and disambiguation**," in *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers*, (Valencia, Spain), pp. 86–98, Association for Computational Linguistics, Apr. 2017.

N. Arefyev, B. Sheludko, A. Podolskiy, and A. Panchenko, "**Always Keep your Target in Mind: Studying Semantics and Improving Performance of Neural Lexical Substitution**," in *Proceedings of the 28th International Conference on Computational Linguistics*, (Barcelona, Spain (Online)), pp. 1242–1255, International Committee on Computational Linguistics, Dec. 2020.

A. Kutuzov, M. Dorgham, O. Oliynyk, C. Biemann, and A. Panchenko, "**Making Fast Graph-based Algorithms with Graph Metric Embeddings**," in *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, (Florence, Italy), pp. 3349–3355, Association for Computational Linguistics, July 2019.

D. Ustalov, N. Arefyev, C. Biemann, and A. Panchenko, "**Negative Sampling Improves Hypernymy Extraction Based on Projection Learning**," in *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers*, (Valencia, Spain), pp. 543–550, Association for Computational Linguistics, Apr. 2017.

R. Aly, S. Acharya, A. Ossa, A. Köhn, C. Biemann, and A. Panchenko, "**Every Child Should Have Parents: A**

Taxonomy Refinement Algorithm Based on Hyperbolic Term Embeddings," in *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, (Florence, Italy), pp. 4811–4817, Association for Computational Linguistics, July 2019.

D. Ustalov, A. Panchenko, C. Biemann, and S. P. Ponzetto, "**Watset: Local-Global Graph Clustering with Applications in Sense and Frame Induction**," *Computational Linguistics*, vol. 45, pp. 423–479, Sept. 2019.

S. Faralli, A. Panchenko, C. Biemann, and S. P. Ponzetto, "**Linked Disambiguated Distributional Semantic Networks**," in *The Semantic Web - ISWC 2016 - 15th International Semantic Web Conference, Kobe, Japan, October 17-21, 2016, Proceedings, Part II* (P. Groth, E. Simperl, A. J. G. Gray, M. Sabou, M. Krötzsch, F. Lécué,

F. Flöck, and Y. Gil, eds.), vol. 9982 of *Lecture Notes in Computer Science*, pp. 56–64, 2016.

C. Biemann, S. Faralli, A. Panchenko, and S. P. Ponzetto, "**A framework for enriching lexical semantic resources with distributional semantics**," *Nat. Lang. Eng.*, vol. 24, no. 2, pp. 265–312, 2018.

D. Ustalov, A. Panchenko, and C. Biemann, "**Watset: Automatic Induction of Synsets from a Graph of Synonyms**," in *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, (Vancouver, Canada), pp. 1579–1590, Association for Computational Linguistics, July 2017.

D. Ustalov, A. Panchenko, A. Kutuzov, C. Biemann, and S. P. Ponzetto, "**Unsupervised Semantic Frame Induction using Triclustering**," in *Proceedings of the 56th Annual Meeting of* *the Association for Computational Linguistics (Volume 2: Short Papers)*, (Melbourne, Australia), pp. 55–62, Association for Computational Linguistics, July 2018.

Ö. Sevgili, A. Shelmanov, M. Y. Arkhipov, A. Panchenko, and C. Biemann, "**Neural entity linking: A survey of models based on deep learning**," *Semantic Web*, vol. 13, no. 3, pp. 527–570, 2022.

S. Anwar, A. Shelmanov, N. Arefyev, A. Panchenko, and C. Biemann, "**Text augmentation for semantic frame induction and parsing**," *Language Resources and Evaluation*, vol. 23, no. 3, pp. 527–556, 2023.

A. Jana, D. Puzyrev, A. Panchenko, P. Goyal, C. Biemann, and A. Mukherjee, "**On the Compositionality Prediction of Noun Phrases using Poincaré Embeddings**," in *Proceedings of the 57th Annual Meeting of the Association for*

Computational Linguistics, (Florence, Italy), pp. 3263–3274, Association for Computational Linguistics, July 2019.

I. Nikishina, V. Logacheva, A. Panchenko, and N. Loukachevitch, "**Studying Taxonomy Enrichment on Diachronic WordNet Versions**," in *Proceedings of the 28th International Conference on Computational Linguistics*, (Barcelona, Spain (Online)), pp. 3095–3106, International Committee on Computational Linguistics, Dec. 2020.

I. Nikishina, M. Tikhomirov, V. Logacheva, Y. Nazarov, A. Panchenko, and N. V. Loukachevitch, "**Taxonomy enrichment with text and graph vector representations**," *Semantic Web*, vol. 13, no. 3, pp. 441–475, 2022.

S. Faralli, A. Panchenko, C. Biemann, and S. P. Ponzetto, "**The ContrastMedium Algorithm: Taxonomy Induction From Noisy Knowledge Graphs With Just A Few Links**," in *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers*, (Valencia, Spain), pp. 590–600, Association for Computational Linguistics, Apr. 2017.

M. Pelevina, N. Arefiev, C. Biemann, and A. Panchenko, "**Making Sense of Word Embeddings**," in *Proceedings of the 1st Workshop on Representation Learning for NLP*, (Berlin, Germany), pp. 174–183, Association for Computational Linguistics, Aug. 2016.

A. Panchenko, F. Marten, E. Ruppert, S. Faralli, D. Ustalov, S. P. Ponzetto, and C. Biemann, "**Unsupervised, Knowledge-Free, and Interpretable Word Sense Disambiguation**," in *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, (Copenhagen, Denmark), pp. 91–96, Association for Computational Linguistics, Sept. 2017.

- A. Panchenko, D. Ustalov, S. Faralli, S. P. Ponzetto, and C. Biemann, "**Improving Hypernymy Extraction with Distributional Semantic Classes**," in *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018)*, (Miyazaki, Japan), European Language Resources Association (ELRA), May 2018.

- V. Logacheva, D. Teslenko, A. Shelmanov, S. Remus, D. Ustalov, A. Kutuzov, E. Artemova, C. Biemann, S. P. Ponzetto, and A. Panchenko, "**Word Sense Disambiguation for 158 Languages using Word Embeddings Only**," in *Proceedings of the Twelfth Language Resources and Evaluation Conference*, (Marseille, France), pp. 5943–5952, European Language Resources Association, May 2020.

- A. Panchenko, S. Faralli, E. Ruppert, S. Remus, H. Naets, C. Fairon, S. P. Ponzetto, and C. Biemann, "**TAXI at**

SemEval-2016 Task 13: a Taxonomy Induction Method based on Lexico-Syntactic Patterns, Substrings and Focused Crawling," in *Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016)*, (San Diego, California), pp. 1320–1327, Association for Computational Linguistics, June 2016.

S. Anwar, A. Shelmanov, A. Panchenko, and C. Biemann, "**Generating Lexical Representations of Frames using Lexical Substitution**," in *Proceedings of the Probability and Meaning Conference (PaM 2020)*, (Gothenburg), pp. 95–103, Association for Computational Linguistics, June 2020.

D. Ustalov, A. Panchenko, C. Biemann, and S. P. Ponzetto, "**Unsupervised Sense-Aware Hypernymy Extraction**," in *Proceedings of the 14th Conference on Natural Language Processing, KONVENS 2018, Vienna, Austria, September 19-21, 2018* (A. Barbaresi, H. Biber, F. Neubarth, and

R. Osswald, eds.), pp. 192–201, Österreichische Akademie der Wissenschaften, 2018.

A. Panchenko, A. Lopukhina, D. Ustalov, K. Lopukhin, N. Arefyev, A. Leontyev, and N. V. Loukachevitch, "**RUSSE'2018: A Shared Task on Word Sense Induction for the Russian Language**," in *Proceedings of the 24th International Conference on Computational Linguistics and Intellectual Technologies (Dialogue'2018). Moscow, Russia.*, pp. 192–201, RGGU, 2018.

N. Arefyev, P. Ermolaev, and A. Panchenko, "**How much does a word weigh? Weighting word embeddings for word sense induction**," in *Proceedings of the 24th International Conference on Computational Linguistics and Intellectual Technologies (Dialogue'2018). Moscow, Russia.*, pp. 201–212, RGGU, 2018.

D. Ustalov, D. Teslenko, A. Panchenko, M. Chernoskutov, C. Biemann, and S. P. Ponzetto, "**An Unsupervised Word Sense Disambiguation System for Under-Resourced Languages**," in *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018)*, (Miyazaki, Japan), European Language Resources Association (ELRA), May 2018.

S. Faralli, A. Panchenko, C. Biemann, and S. P. Ponzetto, "**Enriching Frame Representations with Distributionally Induced Senses**," in *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018)*, (Miyazaki, Japan), European Language Resources Association (ELRA), May 2018.

Ö. Sevgili, A. Panchenko, and C. Biemann, "**Improving Neural Entity Disambiguation with Graph Embeddings**," in *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics: Student Research Workshop*, (Florence, Italy), pp. 315–322, Association for Computational Linguistics, July 2019.

A. Panchenko, "**Best of Both Worlds: Making Word Sense Embeddings Interpretable**," in *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC'16)*, (Portorož, Slovenia), pp. 2649–2655, European Language Resources Association (ELRA), May 2016.

D. Ustalov, M. Chernoskutov, C. Biemann, and A. Panchenko, "**Fighting with the Sparsity of Synonymy Dictionaries for Automatic Synset Induction**," in *Analysis of Images, Social Networks and Texts - 6th International Conference, AIST 2017, Moscow, Russia, July 27-29, 2017, Revised Selected Papers* (W. M. P. van der Aalst, D. I. Ignatov, M. Y. Khachay, S. O. Kuznetsov, V. S. Lempitsky, I. A. Lomazova, N. V.

Loukachevitch, A. Napoli, A. Panchenko, P. M. Pardalos, A. V. Savchenko, and S. Wasserman, eds.), vol. 10716 of *Lecture Notes in Computer Science*, pp. 94–105, Springer, 2017.

A. Panchenko, J. Simon, M. Riedl, and C. Biemann, "**Noun Sense Induction and Disambiguation using Graph-Based Distributional Semantics**," in *Proceedings of the 13th Conference on Natural Language Processing, KONVENS 2016, Bochum, Germany, September 19-21, 2016* (S. Dipper, F. Neubarth, and H. Zinsmeister, eds.), vol. 16 of *Bochumer Linguistische Arbeitsberichte*, 2016.

D. Puzyrev, A. Shelmanov, A. Panchenko, and E. Artemova, "**Noun Compositionality Detection Using Distributional Semantics for the Russian Language**," in *Analysis of Images, Social Networks and Texts - 8th International Conference, AIST 2019, Kazan, Russia, July 17-19, 2019, Revised Selected Papers* (W. M. P. van der Aalst, V. Batagelj,

D. I. Ignatov, M. Y. Khachay, V. V. Kuskova, A. Kutuzov, S. O. Kuznetsov, I. A. Lomazova, N. V. Loukachevitch, A. Napoli, P. M. Pardalos, M. Pelillo, A. V. Savchenko, and E. Tutubalina, eds.), vol. 11832 of *Lecture Notes in Computer Science*, pp. 218–229, Springer, 2019.

N. Arefyev, B. Sheludko, and A. Panchenko, "**Combining Lexical Substitutes in Neural Word Sense Induction**," in *Proceedings of the International Conference on Recent Advances in Natural Language Processing (RANLP 2019)*, (Varna, Bulgaria), pp. 62–70, INCOMA Ltd., Sept. 2019.

A. Kutuzov, M. Dorgham, O. Oliynyk, C. Biemann, and A. Panchenko, "**Learning Graph Embeddings from WordNet-based Similarity Measures**," in *Proceedings of the Eighth Joint Conference on Lexical and Computational Semantics (*SEM 2019)*, (Minneapolis, Minnesota), pp. 125–135, Association for Computational Linguistics, June 2019.

A. Razzhigaev, N. Arefyev, and A. Panchenko, "**SkoltechNLP at SemEval-2021 Task 2: Generating Cross-Lingual Training Data for the Word-in-Context Task**," in *Proceedings of the 15th International Workshop on Semantic Evaluation (SemEval-2021)*, (Online), pp. 157–162, Association for Computational Linguistics, Aug. 2021.

D. Puzyrev, A. Shelmanov, A. Panchenko, and E. Artemova, "**A Dataset for Noun Compositionality Detection for a Slavic Language**," in *Proceedings of the 7th Workshop on Balto-Slavic Natural Language Processing*, (Florence, Italy), pp. 56–62, Association for Computational Linguistics, Aug. 2019.

N. Arefyev, B. Sheludko, A. Davletov, D. Kharchev, A. Nevidomsky, and A. Panchenko, "**Neural GRANNy at**

SemEval-2019 Task 2: A combined approach for better modeling of semantic relationships in semantic frame induction," in *Proceedings of the 13th International Workshop on Semantic Evaluation*, (Minneapolis, Minnesota, USA), pp. 31–38, Association for Computational Linguistics, June 2019.

S. Anwar, D. Ustalov, N. Arefyev, S. P. Ponzetto, C. Biemann, and A. Panchenko, "**HHMM at SemEval-2019 Task 2: Unsupervised Frame Induction using Contextualized Word Embeddings**," in *Proceedings of the 13th International Workshop on Semantic Evaluation*, (Minneapolis, Minnesota, USA), pp. 125–129, Association for Computational Linguistics, June 2019.

A. Panchenko, S. Faralli, S. P. Ponzetto, and C. Biemann, "**Using Linked Disambiguated Distributional Networks for Word Sense Disambiguation**," in *Proceedings of the 1st*

Workshop on Sense, Concept and Entity Representations and their Applications, (Valencia, Spain), pp. 72–78, Association for Computational Linguistics, Apr. 2017.

I. Nikishina, I. Andrianov, A. Vakhitova, and A. Panchenko, "TaxFree: a visualization tool for candidate-free taxonomy enrichment," in *Proceedings of the 2nd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 12th International Joint Conference on Natural Language Processing: System Demonstrations* (W. Buntine and M. Liakata, eds.), (Taipei, Taiwan), pp. 39–47, Association for Computational Linguistics, Nov. 2022.

I. Nikishina, N. Loukachevitch, V. Logacheva, and A. Panchenko, "**Evaluation of Taxonomy Enrichment on Diachronic WordNet Versions**," in *Proceedings of the 11th Global Wordnet Conference*, (University of South Africa

(UNISA)), pp. 126–136, Global Wordnet Association, Jan. 2021.

I. Nikishina, A. Vakhitova, E. Tutubalina, and A. Panchenko, "**Cross-Modal Contextualized Hidden State Projection Method for Expanding of Taxonomic Graphs**," in *Proceedings of TextGraphs-16: Graph-based Methods for Natural Language Processing*, (Gyeongju, Republic of Korea), pp. 11–24, Association for Computational Linguistics, Oct. 2022.

R. Fu, J. Guo, B. Qin, W. Che, H. Wang, and T. Liu, "Learning Semantic Hierarchies via Word Embeddings," in *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, (Baltimore, MD, USA), pp. 1199–1209, Association for Computational Linguistics, 2014.

M. Peters, M. Neumann, M. Iyyer, M. Gardner, C. Clark, K. Lee, and L. Zettlemoyer, "Deep Contextualized Word Representations," in *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, (New Orleans, Louisiana), pp. 2227–2237, Association for Computational Linguistics, June 2018.

J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," in *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, (Minneapolis, Minnesota), pp. 4171–4186, Association for Computational Linguistics, June 2019.

Z. Yang, Z. Dai, Y. Yang, J. Carbonell, R. R. Salakhutdinov, and Q. V. Le, "Xlnet: Generalized autoregressive pretraining for language understanding," in *Advances in neural information processing systems*, pp. 5753–5763, 2019.