Towards the Automatic Creation of a Wordnet from a Term-based Lexical Network

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1. Introduction
   - Lexical ontologies
   - Information extraction
   - Issues
   - Research Goals
2. Approach
   - Clustering for synsets
   - Merging thesauri
   - Assigning terms to synsets
3. Experimentation
   - Preparation
   - Wordnet establishment
4. Concluding remarks

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  - Knowledge structured on words and their meanings
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- Construction and maintenance involve time-consuming human effort!

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  1. **basketball**, noun – *a game, also known as hoops, played indoors...*
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- From textual corpora:
  - *... team sports, such as basketball, rugby ...*
    → *team_sport* HYPERNYM_OF *basketball*
    → *team_sport* HYPERNYM_OF *rugby*

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- An example extracted from a Portuguese dictionary:
  ruína SYNONYM_OF *queda* $\wedge$ *queda* SYNONYM_OF *habilidade* $\rightarrow$ *habilidade* SYNONYM_OF *ruína* ??
- *queda* can either mean *aptitude* or *downfall*!

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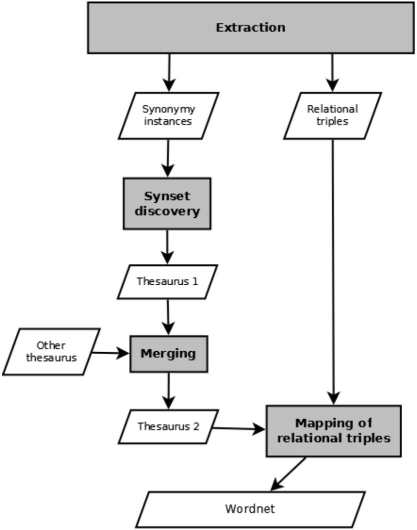
  - Synsets: groups of synonymous words
  - Synset-based relational triples
- WSD based on the knowledge already extracted, not on the context.

Information flow



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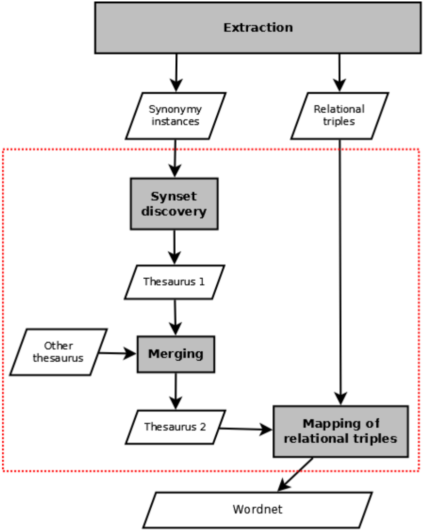
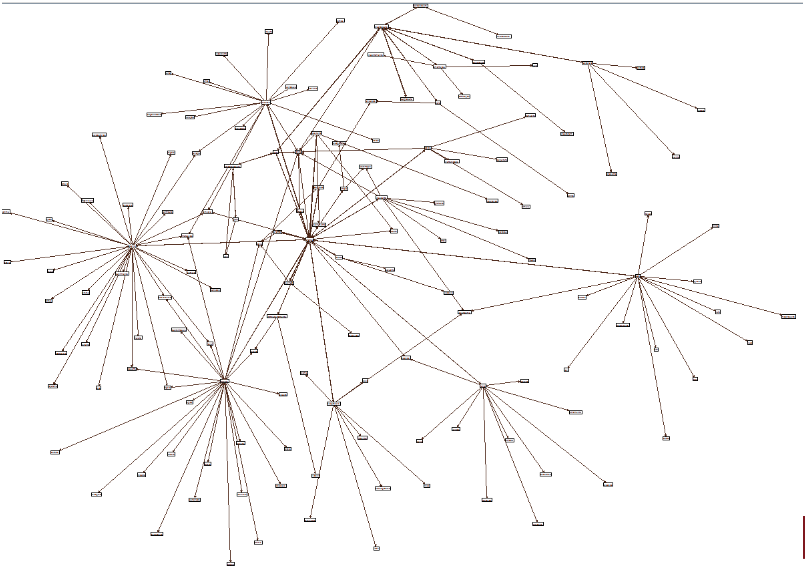


Synonymy networks tend to have a clustered structure



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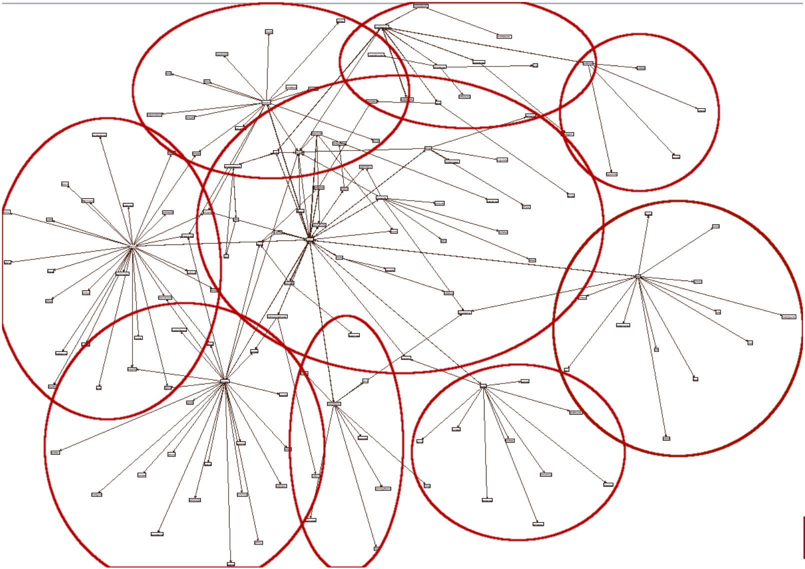

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4. Use the (hard) clustering from each run to create P, a matrix with the probabilities of each pair of words in F belonging to the same cluster;
5. Remove: (a) big clusters, B, if there is a group of clusters $C = C_1, C_2, ... C_n$ such that $B = C_1 \cup C_2 \cup ... \cup C_n$; (b) clusters completely included in other clusters.

Merging synsets from different thesaurus

For each synset $T_i \in T$, select $B_j \in B$ with higher $c = T_i \cap B_j / T_i \cup B_j$[1]

- $B_1 = (diva, beldade, beleza, deidade, deusa, divindade)$
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- $N = B_1 \cup T_1 = (diva, beldade, beleza, deidade, deusa, divindade)$

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Mapping methods

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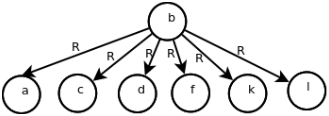
- Output: semantic network W, whose nodes are synsets, which relate to other synsets by means of semantic relations (wordnet)

Procedure 1

Assignment of a (in $a\ R\ b$) to A:

1. Fix b



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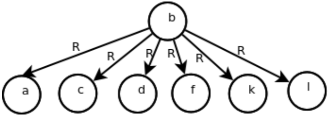

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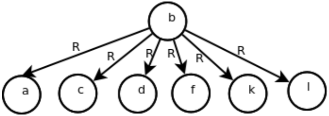

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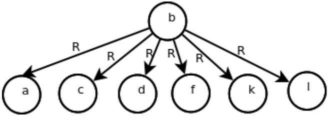

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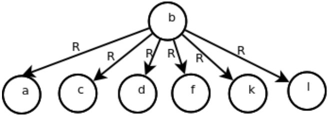

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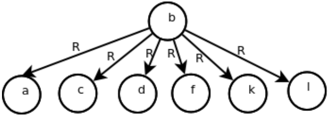

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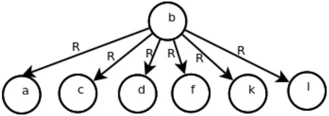

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   - $a \rightarrow S_{a1}$

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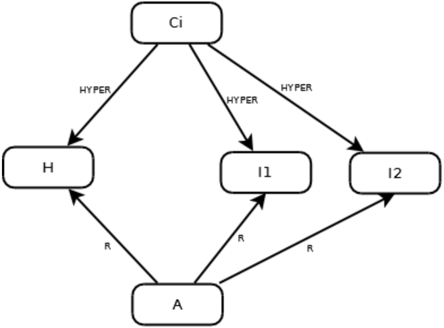
- Assigning b in $A\ R\ b$

Procedure 1 (stage 2) – examples and additional cleaning

If there is $C_i \in C$ with...

- C_i HYPER_OF $H \wedge A\ R\ H$, $b \rightarrow C_i$

  If all C_i HYPER_OF $I_i \wedge A\ R\ I_i$, triples $A\ R\ I_i$ can be inferred!



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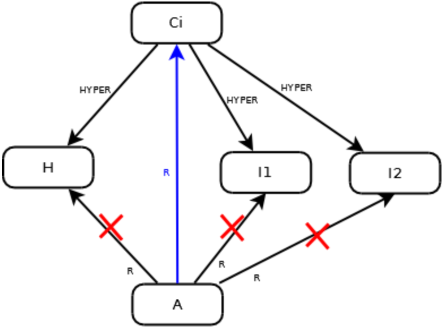

- If $H = (dog)$ $I_1 = (cat)$, $I_1 = (mouse)$ and $C_i = (mammal)$:
  - $A = (hair)$ and $R = (PART\_OF)$
  - $A = (animal)$ and $R = (HYPER\_OF)$

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$$sim(A, B) = \frac{\sum_{i=1}^{|A|} \sum_{j=1}^{|B|} \cos(A_i, B_j)}{|A||B|}$$

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4. Select the pair of synsets with the highest similarity

Resources used (only nouns)

- PAPEL[2] lexical network

[2] http://www.linguateca.pt/PAPEL/
[3] http://www.nilc.icmc.usp.br/tep2/index.htm
[4] http://openthesaurus.caixamagica.pt/

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- TeP[3] thesaurus
- OpenThesaurus.PT (OT)[4]

- CLIP = clustered PAPEL
- TOP = TeP merged with OT, merged with CLIP

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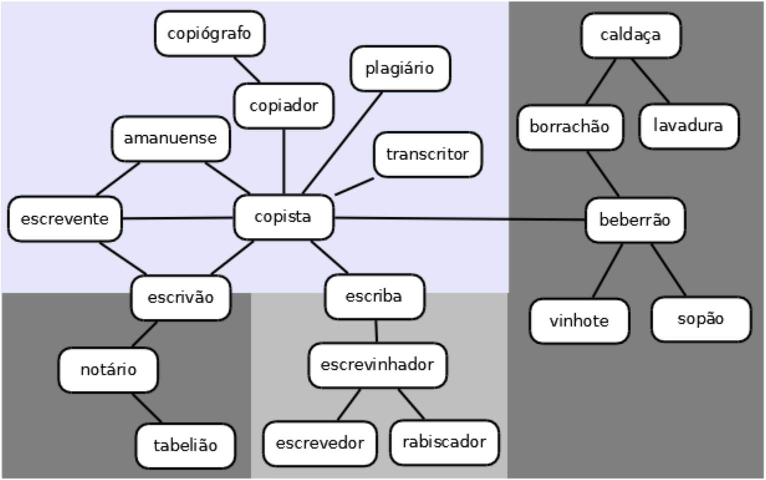
Resulting Thesaurus

		TeP	OT	CLIP	TOP
Words	**Quantity**	17,158	5,819	23,741	30,554
	Ambiguous	5,867	442	12,196	13,294
	Most ambiguous	20	4	47	21
Synsets	**Quantity**	8,254	1,872	7,468	9,960
	Avg. size	3.51	3.37	12.57	6.6
	Biggest	21	14	103	277

Table: (Noun) thesauruses in numbers.

Clustered sub-network of PAPEL – example



Manual validation

	Sample	Correct	Incorrect	N/A	Agreement
CLIP	519 sets	65.8%	31.7%	2.5%	76.1%
CLIP'	310 sets	81.1%	16.9%	2.0%	84.2%
TOP	480 sets	83.2%	15.8%	1.0%	82.3%
TOP'	448 sets	86.8%	12.3%	0.9%	83.0%

Table: Results of manual synset validation.

- CLIP' and TOP' only consider synsets with 10 or less words.
  - The quality is higher for smaller synsets.

Resulting WordNet

		Hypernym_of	Part_of	Member_of
Term-based triples		62,591	2,805	5,929
1st	**Mapped**	27,750	1,460	3,962
	Same synset	233	5	12
	Already present	3,970	40	167
Semi-mapped triples		7,952	262	357
2nd	**Mapped**	88	1	0
	Could be inferred	50	0	0
	Already present	13	0	0
Synset-based triples		23,572	1,416	3,783

Table: Results of triples mapping

Automatic validation

For each triple, *A R B*

1. Compile a set of textual patterns denoting *R*, e.g.:
   - (hypo) `é um|uma (tipo|forma|variedade|...)* de` (hyper)
   - (whole/group) `é um (grupo|conjunto|...)  de` (part/member)

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2. Score the triple with the help of Google:

$$score = \frac{\sum_{i=1}^{|A|} \sum_{j=1}^{|B|} found(A_i, B_j, R)}{|A| * |B|}$$

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Relation	Sample size	Validation
Hypernymy_of	419 synsets	44,1%
Member_of	379 synsets	24,3%
Part_of	290 synsets	24,8%

Table: Automatic validation of triples

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  - Clustering is a suitable alternative for establishing synsets
    - What about for networks not extracted from dictionaries?
  - Rules can be defined to map terms in triples to synsets
    - Though some triples remain unmapped...
- Future:
  - Evaluate the alternative mapping method
  - Exploit other resources: e.g. Wiktionary and Wikipedia

References

Christiane Fellbaum, editor (1998).
WordNet: An Electronic Lexical Database (Language, Speech, and Communication).
The MIT Press.

Graeme Hirst (2004).
Ontology and the lexicon.
In Steffen Staab and Rudi Studer, editors, *Handbook on Ontologies*, International Handbooks on Information Systems, pages 209–230. Springer.

S. M. van Dongen (2000).
Graph Clustering by Flow Simulation.
Ph.D. thesis, University of Utrecht.

David Gfeller, Jean-Cédric Chappelier and Paulo De Los Rios (2005).
Synonym Dictionary Improvement through Markov Clustering and Clustering Stability.
In *Proc. of International Symposium on Applied Stochastic Models and Data Analysis (ASMDA)*, pages 106–113.

Thank you!