Onto.PT: Automatic construction of a Lexical Ontology for Portuguese

Hugo Gonçalo Oliveira[1], Paulo Gomes

{hroliv,pgomes}@dei.uc.pt

Cognitive & Media Systems Group
CISUC, University of Coimbra

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  - Knowledge structured on words and their meanings
  - Cover the whole language
  - Not based on a specific domain
- Typically handcrafted...
  - Construction and maintenance involve time-consuming human effort!

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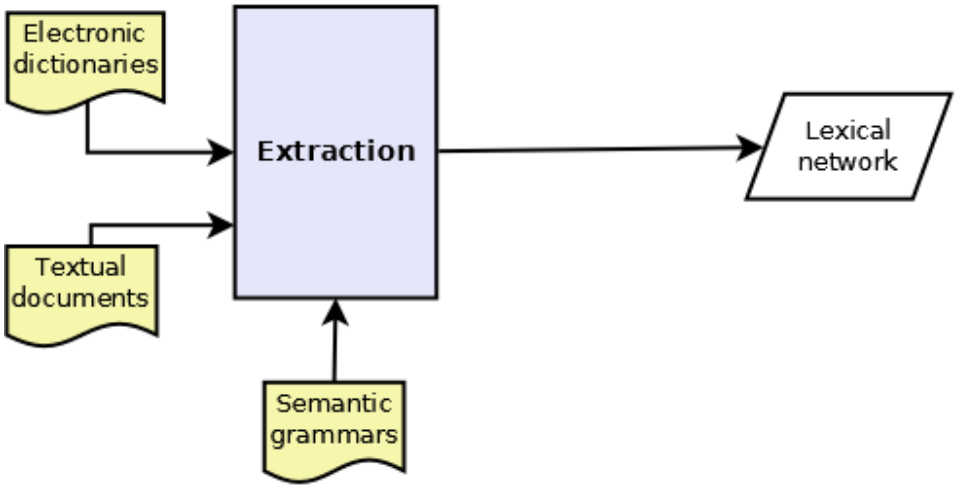
  - Synsets: groups of synonymous words
  - Synset-based relational triples
- WSD based on the knowledge already extracted, not on the context


Electronic dictionaries
Extraction
Lexical network
Textual documents
Semantic grammars

Examples

- From dictionaries:
  - `tenreiro, n -- terneiro, novilho ou bezerro.`
    → *terneiro* SYNONYM_OF *tenreiro*
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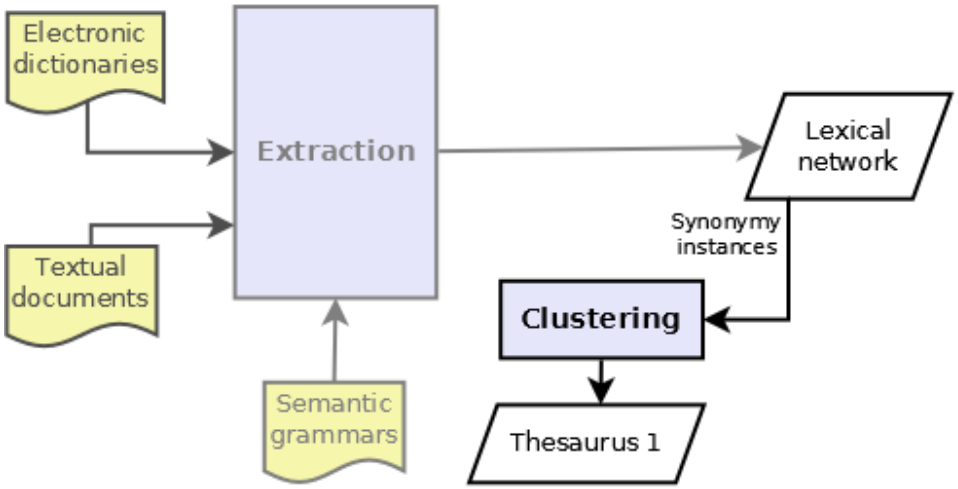
- From textual corpora:
  - `O automobilismo (também conhecido como corridas de automóveis ou desporto motorizado) é um desporto...`
    → *automobilismo* SYNONYM_OF *corridas_de_automóveis*
    → *automobilismo* SYNONYM_OF *desporto_motorizado*
    → *desporto* HYPERNYM_OF *automobilismo*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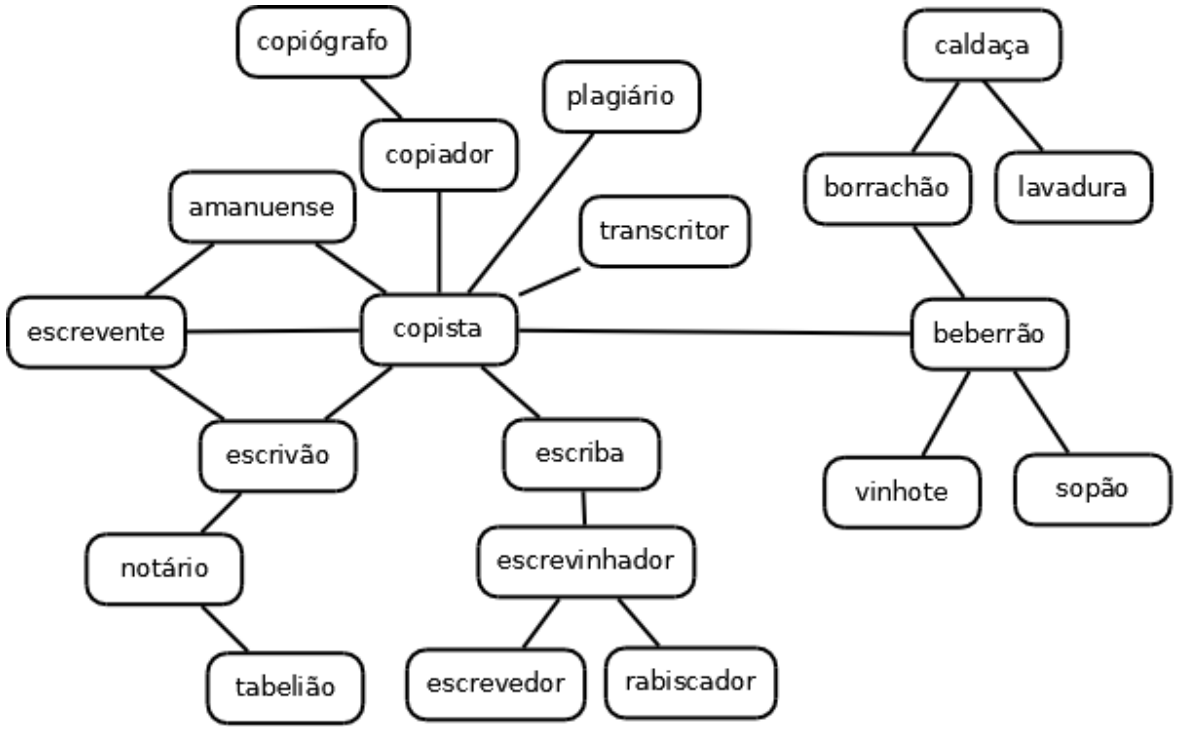
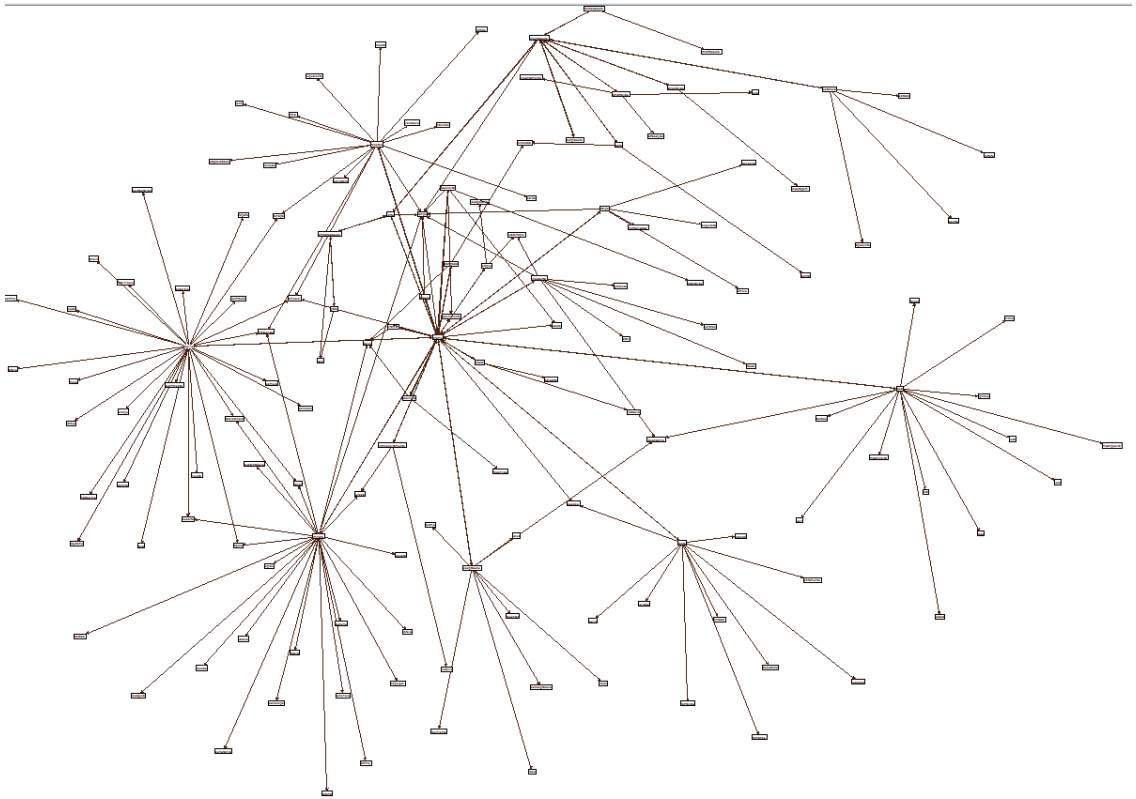
Synonymy lexical network – example



Synonymy networks tend to have a clustered structure



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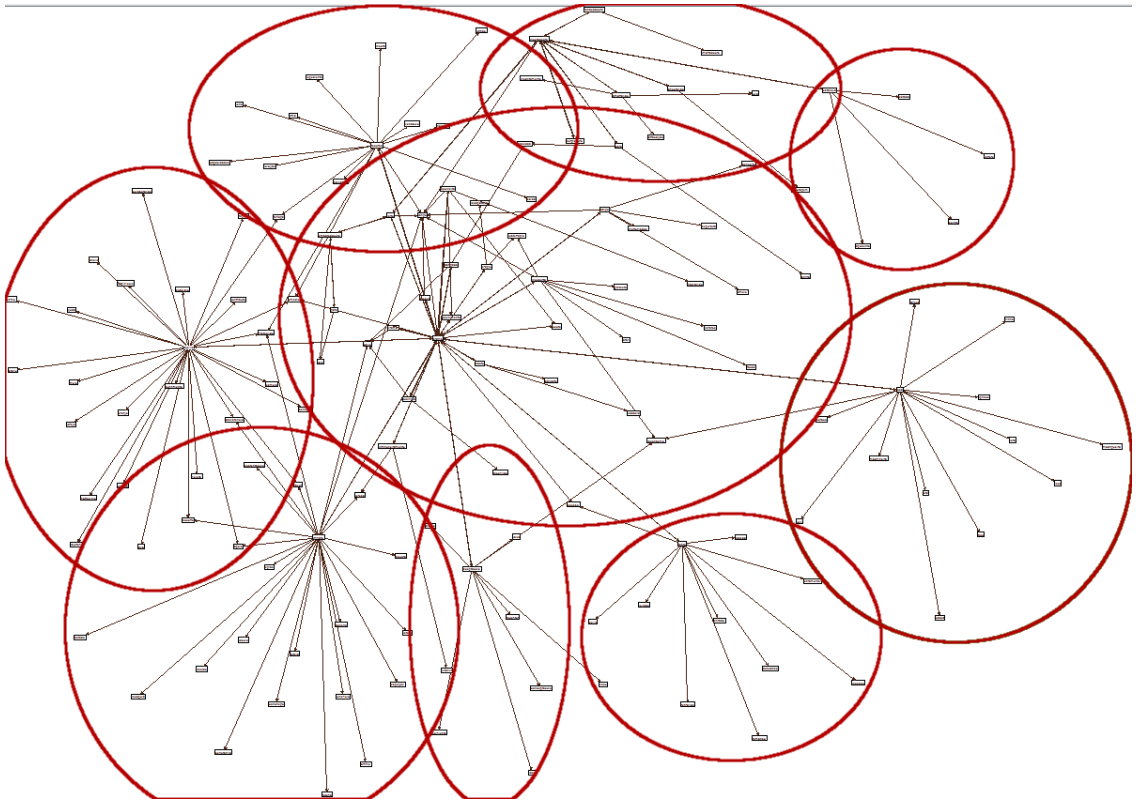

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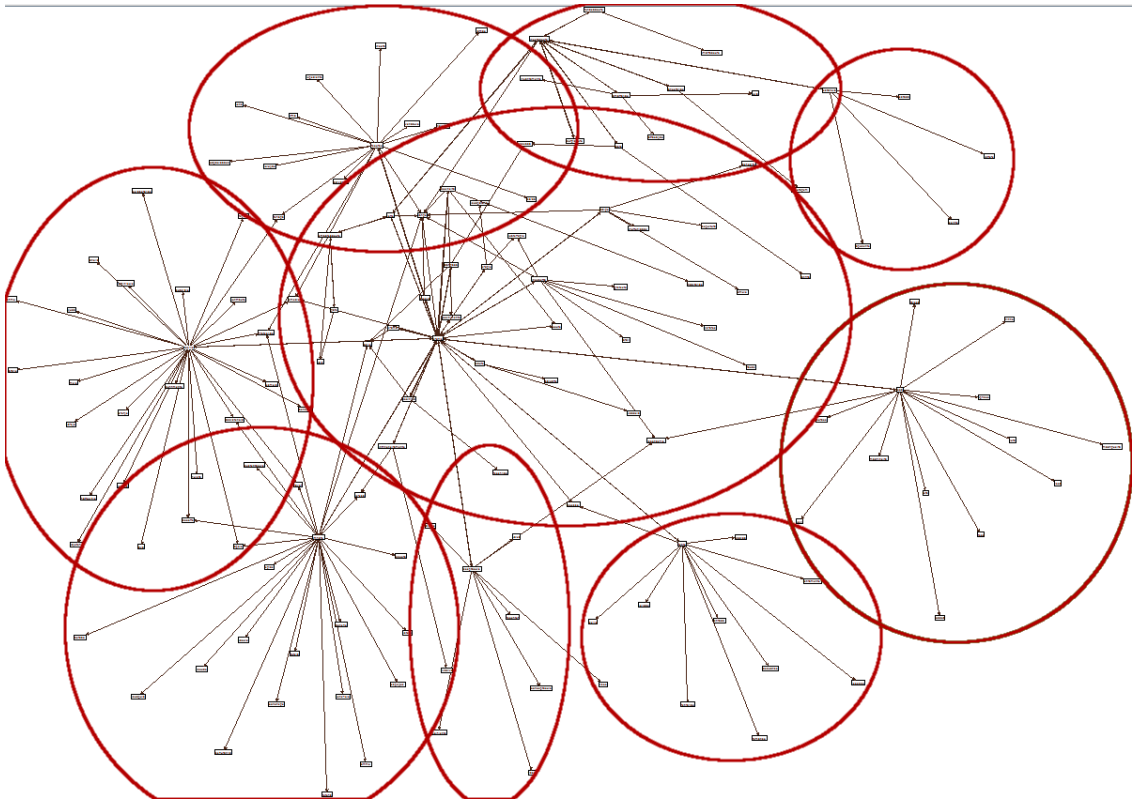

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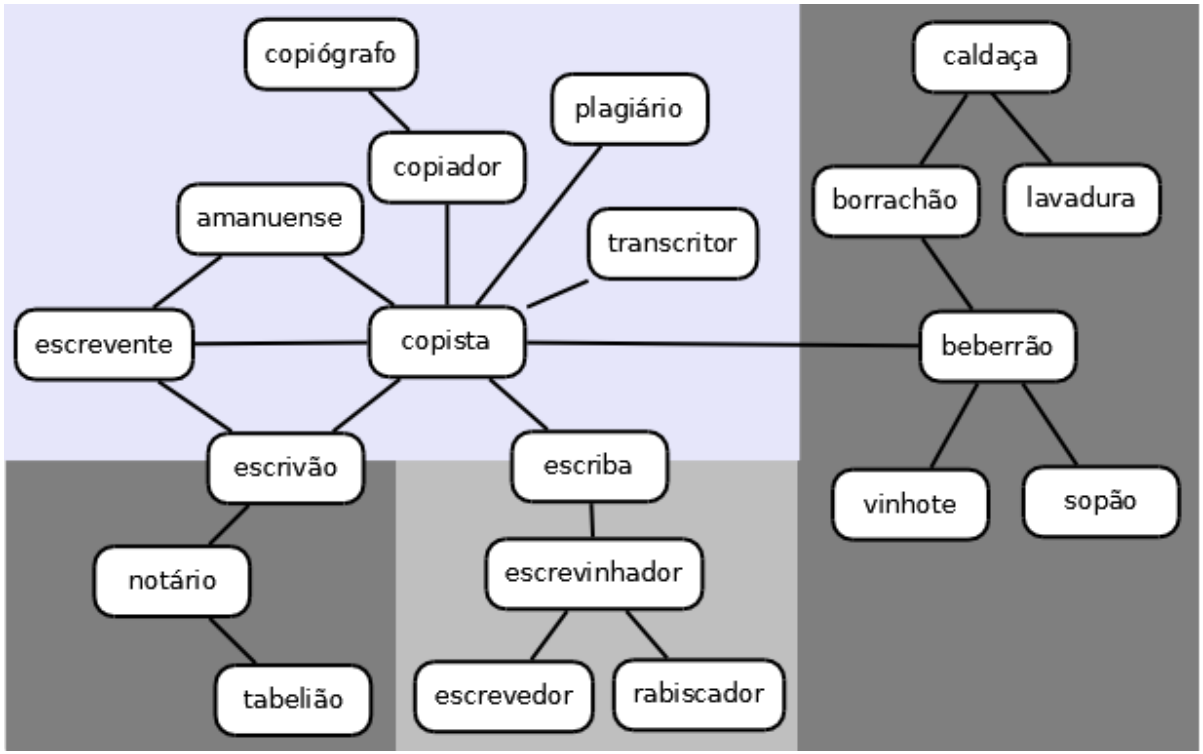
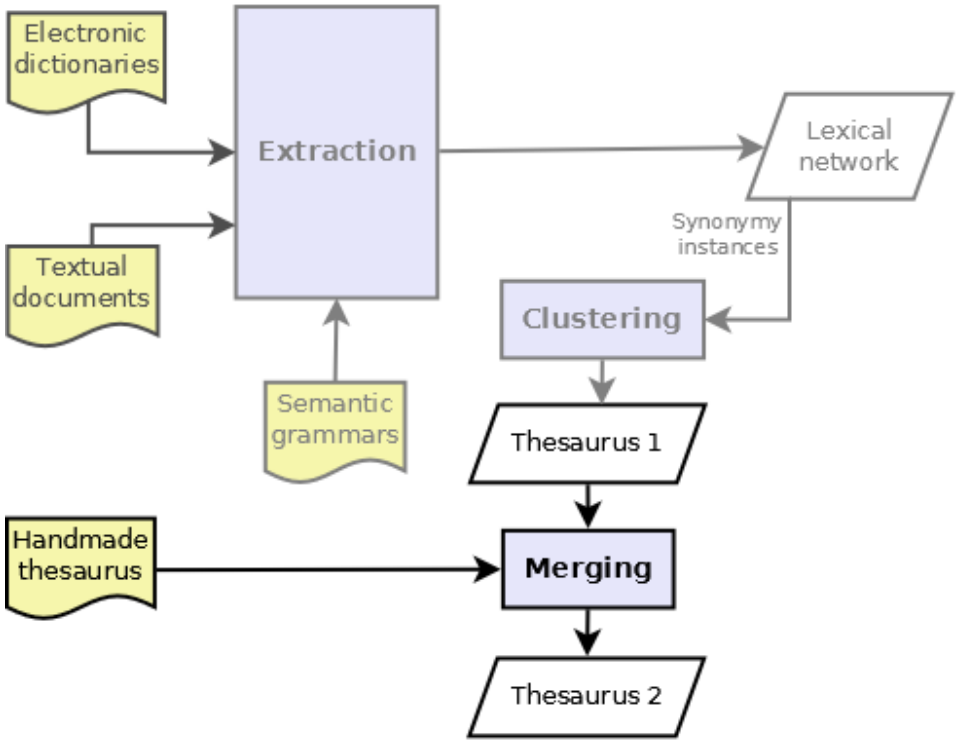
- Keep ambiguity: clusters might be overlapping!

Clustering – example

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Merging synsets from different thesauri

For each synset $T_i \in T$, select $B_j \in B$ with higher $c = T_i \cap B_j / T_i \cup B_j$[2]

- $B_1 = (diva, beldade, beleza, deidade, deusa, divindade)$
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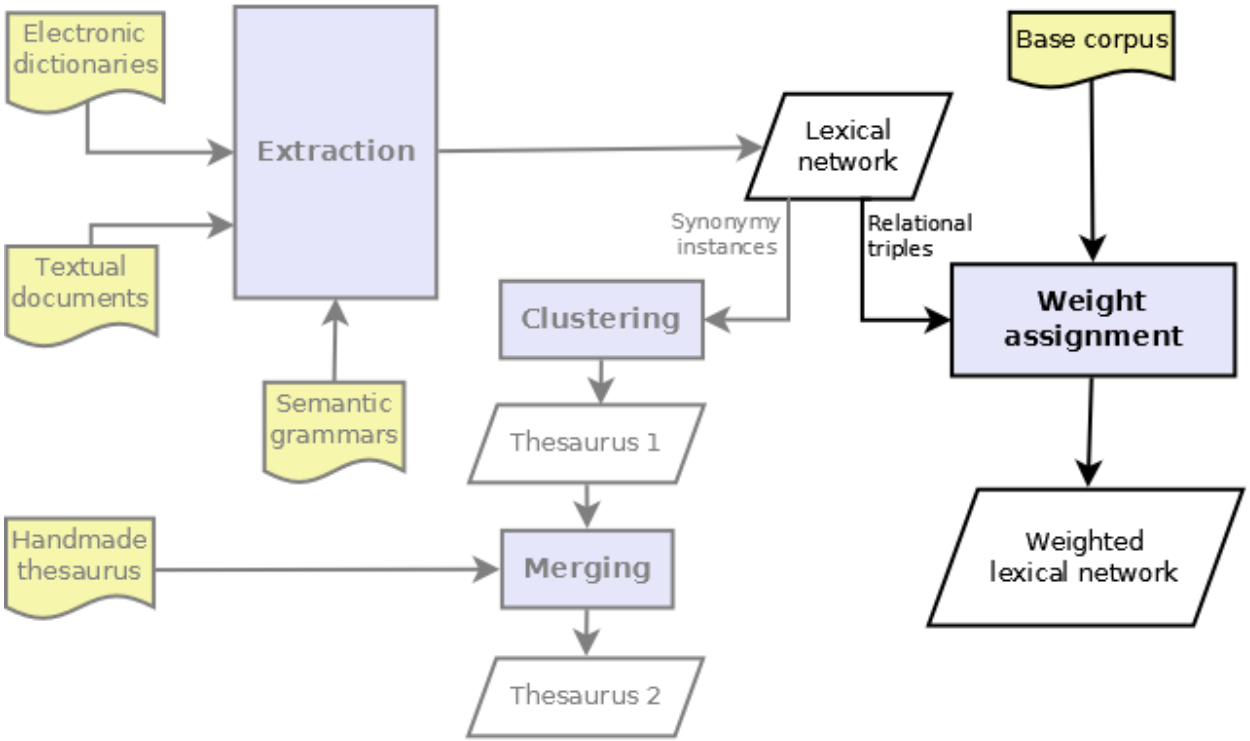
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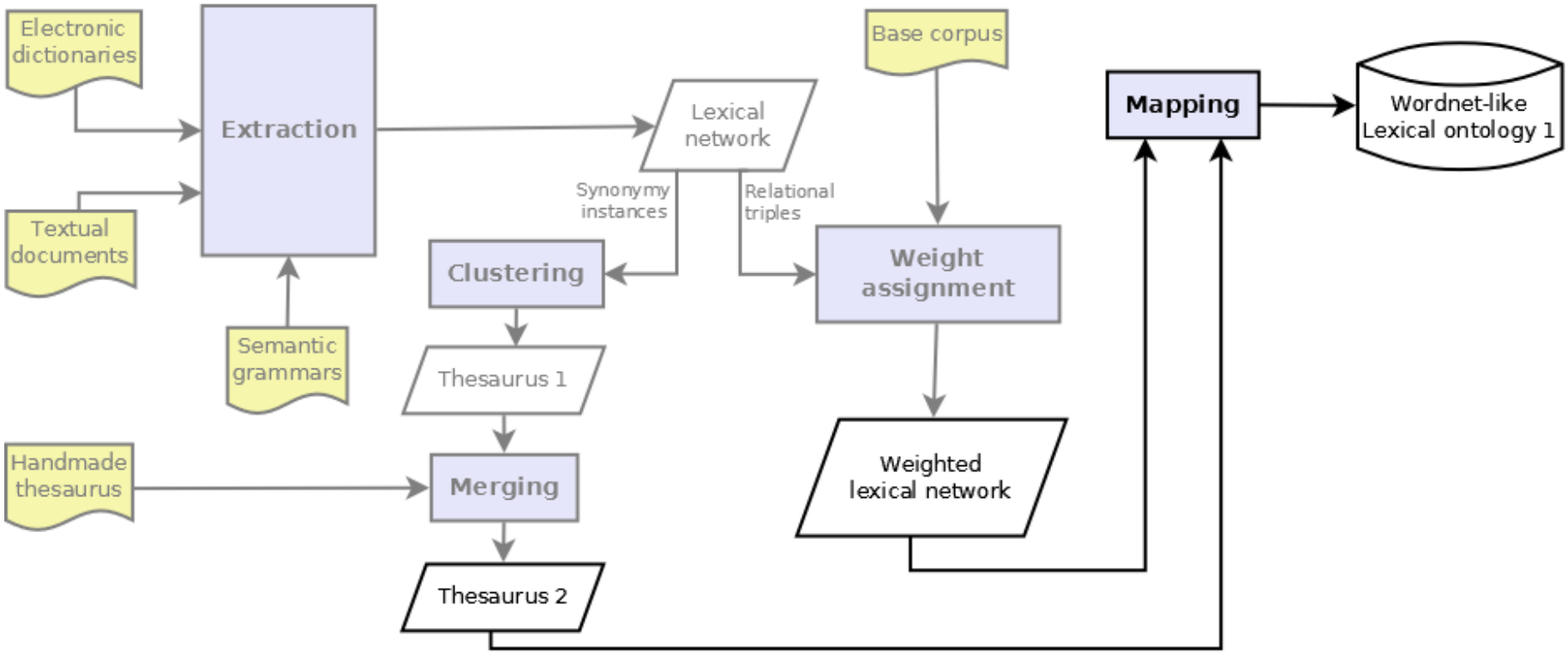
- Define filters based on weights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- Output: semantic network W, whose nodes are synsets, which relate to other synsets by means of semantic relations (wordnet)

Mapping procedures

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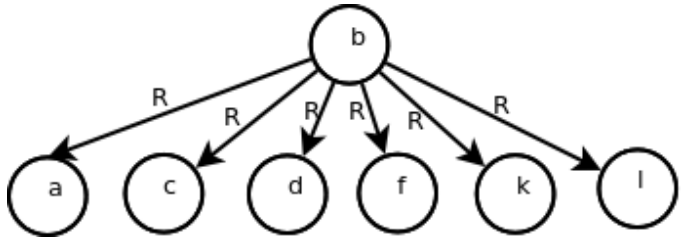

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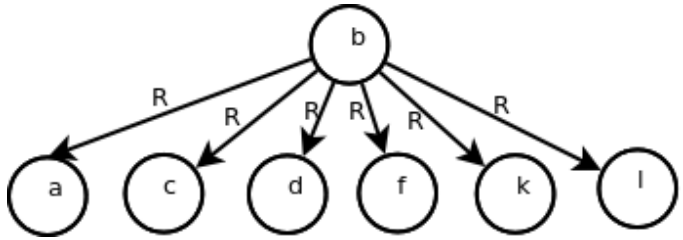

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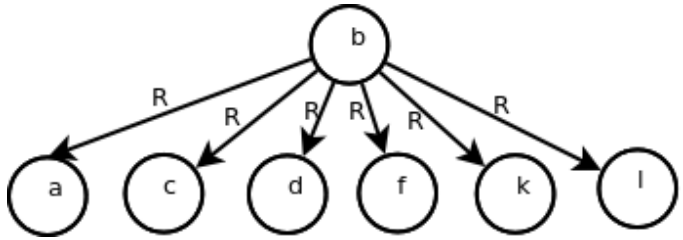

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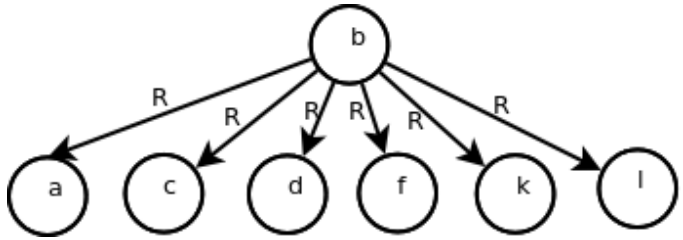

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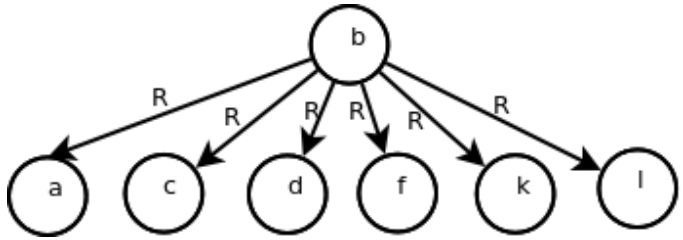

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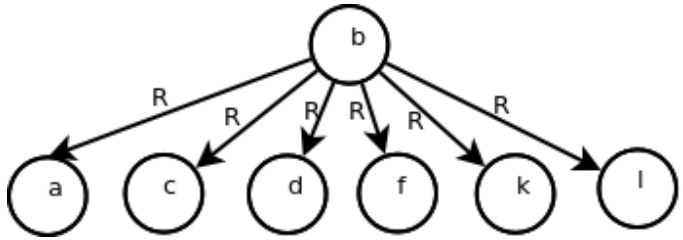

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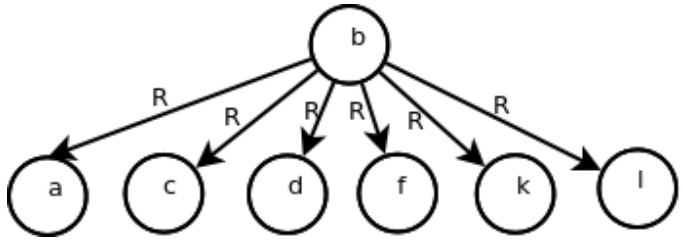

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$$sim(A, B) = \frac{\sum_{i=1}^{|A|} \sum_{j=1}^{|B|} \cos(A_i, B_j)}{|A||B|}$$

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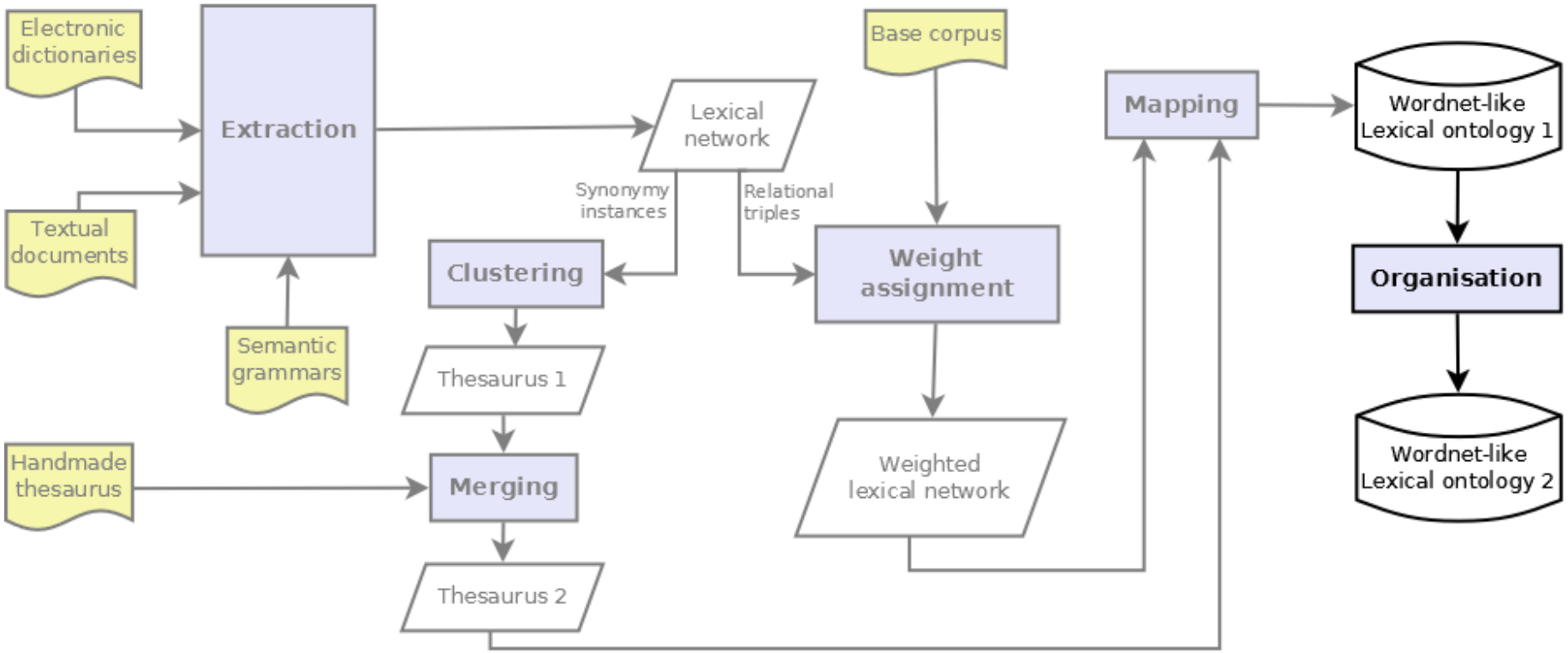
4. Select the pair of synsets with the highest similarity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Knowledge organisation

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- Inheritance
  - if R is not a HYPERNYMY or HYPONYMY relation:
    $(A\ \text{HYPERNYM\_OF}\ B) \wedge (A\ R\ C) \rightarrow (B\ R\ C)$

Triples extracted from dictionaries

- Dicionário da Língua Portguesa (PAPEL 2.0)
- Dicionário Aberto (DA)

Relation	Arguments	PAPEL 2.0	DA	Examples
Synonymy	noun,noun	37,452	20,910	*auxílio, contributo*
	verb,verb	21,465	8,715	*tributar, colectar*
	adj,adj	19,073	7,353	*flexível, moldável*
	adv,adv	1,171	605	*após, seguidamente*
Hypernymy	noun,noun	62,591	59,887	*planta, salva*
Part-of	noun,noun	2,805	1,795	*cauda, cometa*
	noun,adj	3.721	4,902	*tampa, coberto*
Member-of	noun,noun	5.929	1,564	*ervilha, Leguminosas*
	adj,noun	883	59	*celular, célula*
Causation	noun,noun	1.013	264	*fricção, assadura*
	adj,noun	498	166	*reactivo, reacção*
	verb,noun	6,399	5,714	*limpar, purgação*
Purpose	noun,noun	2,886	1,760	*defesa, armadura*
	verb,noun	5,192	3,383	*fazer_rir, comédia*
	verb,adj	260	186	*corrigir, correccional*

Table: Examples of triples

Relations extracted from Wikipedia abstracts

Relation	Quantity	Example	Sample	Correct	Agreement
Synonymy	11,862	*estupro,violação*	286	86,1%	91,2%
Hypernymy	29,563	*estilo_de_música,folk*	322	59,1% [3]	93,1%
Part-of	1,287	*jejuno,intestino*	268	52,6%	78,4%
Causation	520	*parasita,doença*	244	49,6%	79,5%
Purpose	743	*construção,terracota*	264	57,0%	82,2%

Table: Examples and validation of relations

[3] In 30%, grammars/tagger could not identify complete scientific names as in:
O Iriatherina werneri é uma espécie de peixe de aquário
→ *peixe_de_aquário* HYPERNYM_OF *werneri*

Thesaurus

- TeP[4] thesaurus
- OpenThesaurus.PT (OT)[5]
- Clustered PAPEL (CLIP)
- TeP merged with OT, merged with CLIP (TOP)

		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.

[4] http://www.nilc.icmc.usp.br/tep2/index.htm
[5] http://openthesaurus.caixamagica.pt/

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 – related proportion

		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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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 for establishing synsets
  - Disambiguation of terms based on the extracted knowledge
  - Further organisation
- Check `http://ontopt.dei.uc.pt` for updates and available resources

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Thank you!