Towards an Onomasiological Study of Lexical Semantic Change through the Induction of Concepts

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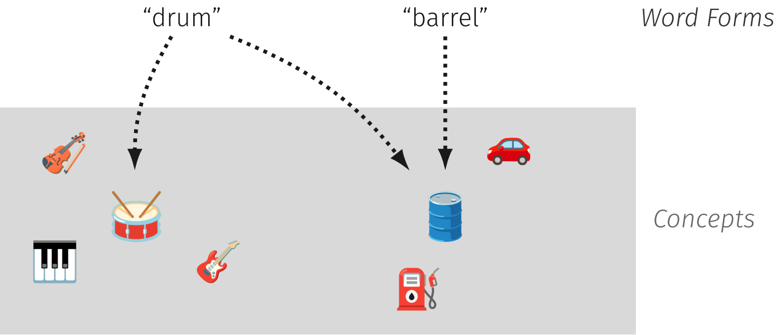
Context

The word-meaning mapping



The Semasiological View of Lexical Semantic Change

Meaning of "drum" before the 19th century.

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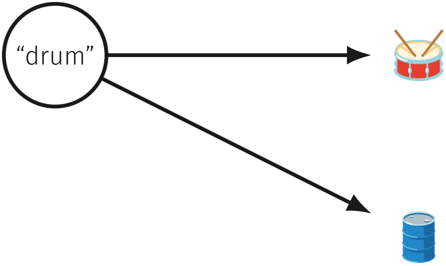

Meaning of “drum” **after** the 19th century.

NLP approach for Semasiological LSC

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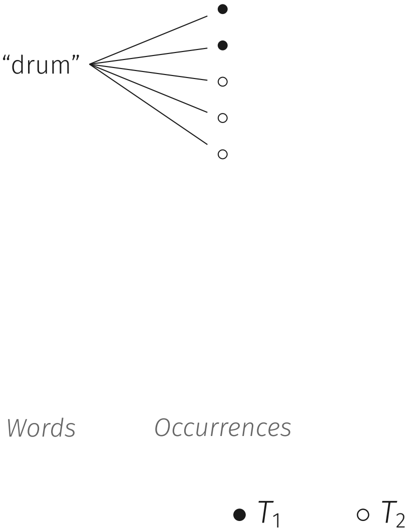
3. **Compare the sense distributions** between pairs of periods T_1 and T_2 (assuming we can *align clusters* from different periods).
   $\rightarrow$ typically using a metric like the *Jensen-Shannon Divergence*.

(Giulianelli et al., 2020; Martinc et al., 2020)

NLP approach for Semasiological LSC (ctd.)



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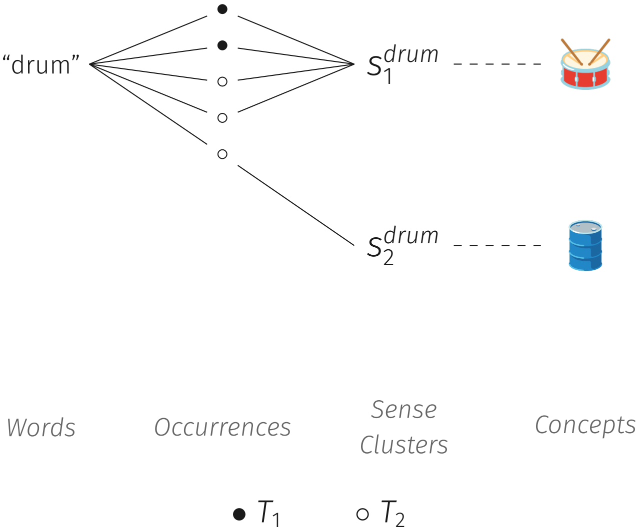
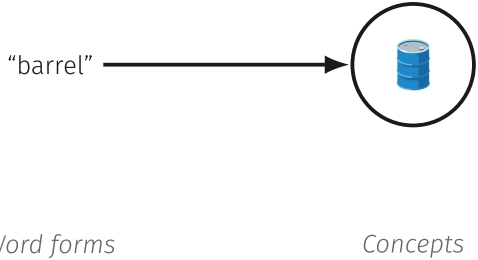


Inducing Concepts for Onomasiological LSC

The Onomasiological View of Semantic Change



Naming of the concept of *large cylindrical container for liquids* before the 19th century.

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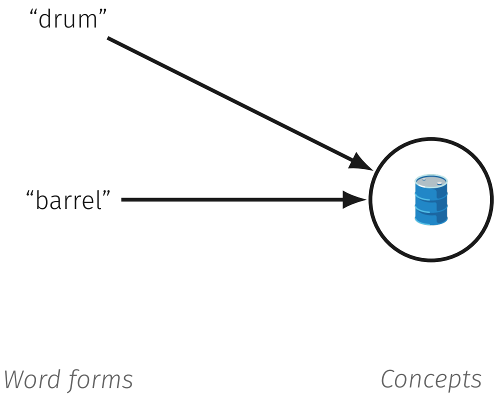

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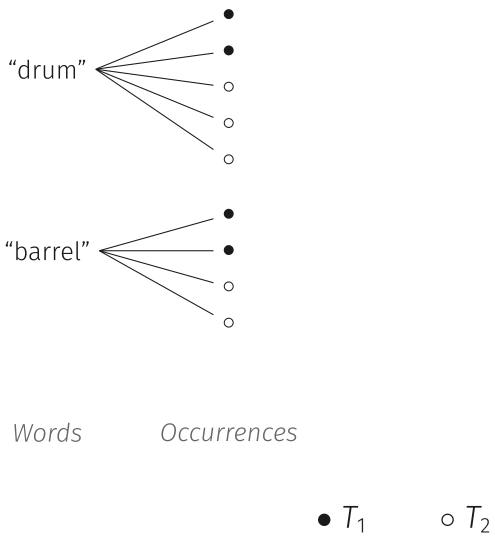
4. Compare **how concept distributions** (of words) or **word inventories** (of concepts) changed, assuming we can align concept clusters over time.

Inducing Concepts with Double-Clustering (ctd.)



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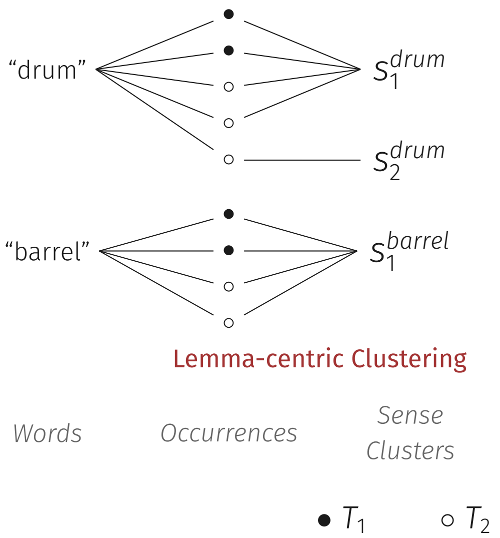

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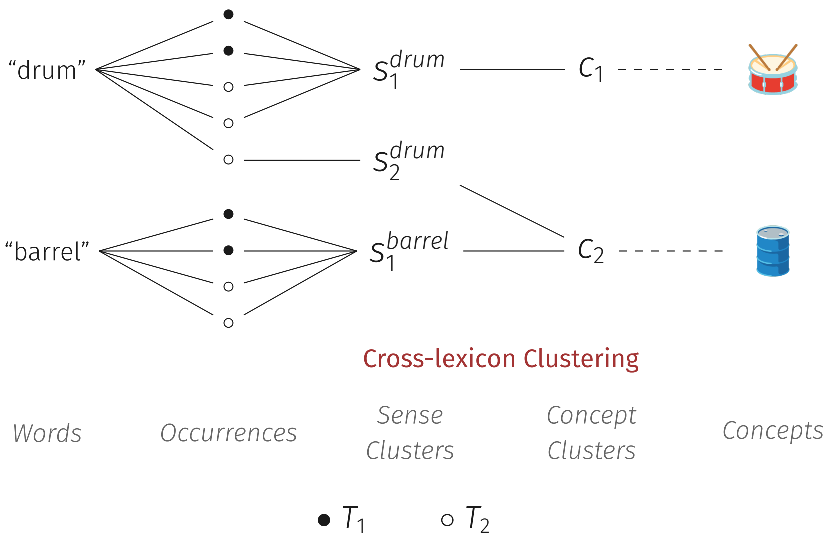

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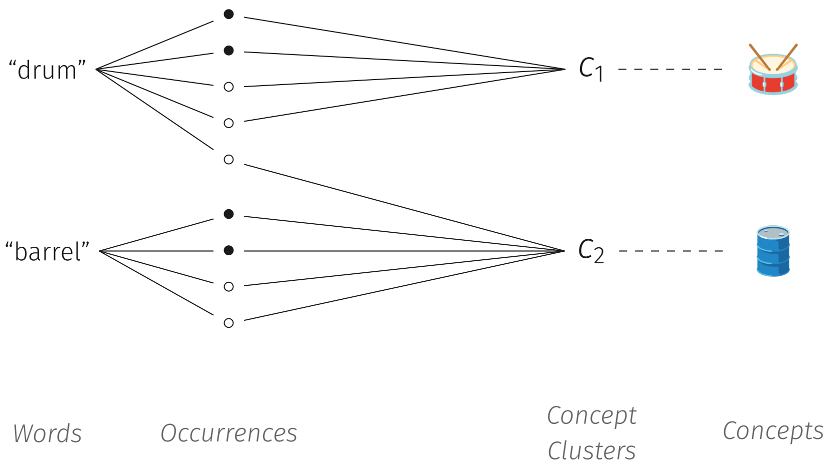


● T_1 ○ T_2

Key Components

1. A **target lexicon** and the corresponding occurrences.
2. A **representation mode** for occurrences.
3. A **lemma-centric clustering** algorithm applied to *occurrences*.
4. A **cross-lexicon clustering** algorithm applied to *sense clusters*.
5. A **temporal cluster alignment** strategy.

Experimental Application

Setup

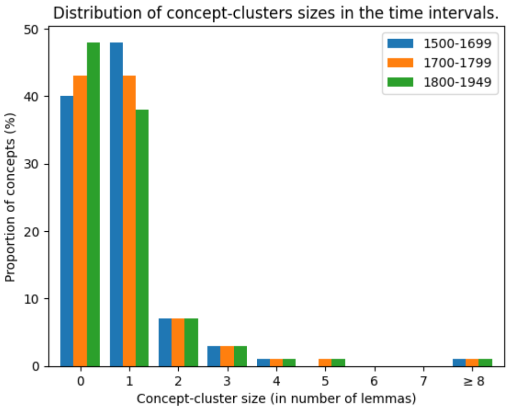
- **Data:** PRESTO (core) Corpus (French, 1500-1950).
  53 texts, various genres, fiction and non-fiction.
- **Target lexicon:** 623 nouns.
  314K occurrences total, occs/word ratio : 504.4
- **Time periods:** 1500-1699, 1700-1799, 1800-1949 (balanced in # of occurrences).
- **Representation mode:**
  - Partial sentence lemmatization (N,V,ADJ, ADV)
  - Embeddings from hidden-layers of XLM-R (Large).

Clustering Strategy

- **Lemma-centric clustering:**
  - Hierarchical Agglomerative (linkage: minimum).
- **Cross-lexicon clustering:**
  - Averaging occurrence vectors in sense clusters
  - Hierarchical Agglomerative (linkage: average).
- **Cluster alignment:** All periods are mixed together during clustering.
- **Algorithms / Hyperparameters selection:** Highest amount of concept clusters containing 2-5 distinct words.

Statistics on Obtained Concept Clusters

867 concept-clusters across the 3 time periods; Only 265 (31%) appear in all 3 periods.



The Single-Word Clusters

In each period, 40% of concept clusters **contain only 1 unique target word**.
It includes 51% of the 265 concept clusters instantiated in all 3 periods.

Clark (1993)'s **Principle of Conventionality**:

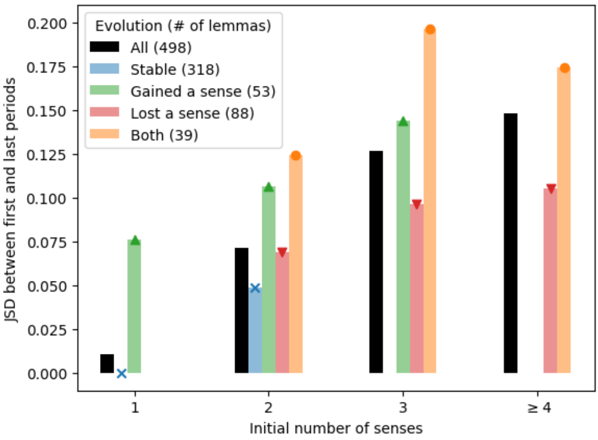
For certain meanings, there is a form that speakers expect to be used in the language community.

Quality of Obtained Clusters in 1800-1949

		Cluster size		
Category	Total	2	3	4
Nb. of clusters	101	62	29	10
Synonyms	27%	32%	24%	0%
Near-synonyms	20%	15%	28%	30%
Lexical / topical relations	40%	42%	38%	40%
Invalid cluster	13%	11%	10%	30%

Table 1: Categorization of small induced concept-clusters in 1800-1949. Invalid clusters are those showing no semantic relation.

Semasiological Lexical Semantic Change



Significant correlation:
- initial # of senses
- JSD

(Law of Innovation, Hamilton et al. 2016; Luo and Xu 2018)

Onomasiological Lexical Semantic Change

Concept Evolution	#Concepts
Expanded naming	27 (10%)
Shrinked naming	5 (2%)
Both	6 (2%)
Identical naming	227 (86%)

Expanded naming: {"peuple", "tribu"} (PEOPLE), {"feu", "incendie"} (BIG FIRE).
Shrinked naming: {"pourquoi", "parquoi"} (EXPLANATION), {"amour", "amitié"} (ROMANTIC LOVE).

Conclusion and Perspectives

In this talk, we introduced a methodology...

- **inducing concepts** from word occurrences,
- with **no requirement** of predefined concepts,
- allowing both **semasiological** and **onomasiological** studies of LSC.

Perspectives:

- More advanced bi-level clustering strategy
- Different time granularity
- Cluster interpretation

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