French Lexical Semantic Graphs: Enrichment by Link Prediction and Integration in a WSD model

Hee-Soo Choi

ANR SELEXINI Meeting

Quick presentation

- 3rd year PhD student in Language Science at ATILF and LORIA, Nancy
- Supervised by Mathieu Constant, Karën Fort and Bruno Guillaume
- MSc and BSc in Linguistics and Computer Science in Sorbonne University, Paris

Main themes of the PhD

- Overview on French lexical resources [Choi, 2022, Choi et al., 2023]
- Enriching French lexical semantic graphs with link prediction [Choi et al., 2024]
- Leveraging linguistic information in graph embeddings
- Improving Word Sense Disambiguation task in French

Beyond Model Performance: Can Link Prediction Enrich French Lexical Graphs?

Hee-Soo Choi, Priyansh Trivedi,
Mathieu Constant, Karën Fort, Bruno Guillaume

LREC-COLING 2024, Turin, Italy

Motivations

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- a resource-oriented approach on two French lexical graphs

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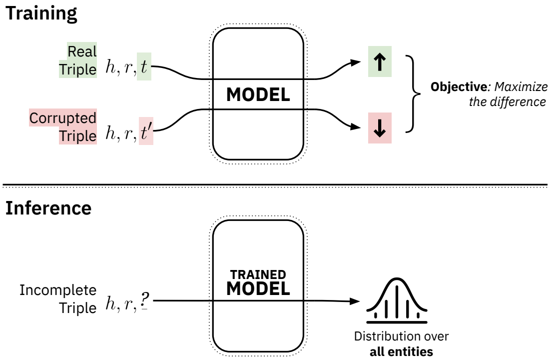
We propose:

- a resource-oriented approach on two French lexical graphs
- to extract new relations from a link prediction model to enrich a sparse lexical graph

Link prediction task

The link prediction task consists in predicting missing triples in a graph described by a set of triples (h, r, t) for head, relation and tail.



REZO and JeuxDeMots [Lafourcade and Joubert, 2008]

- Very dense resource: 6 million nodes and 537 million edges in October 2023
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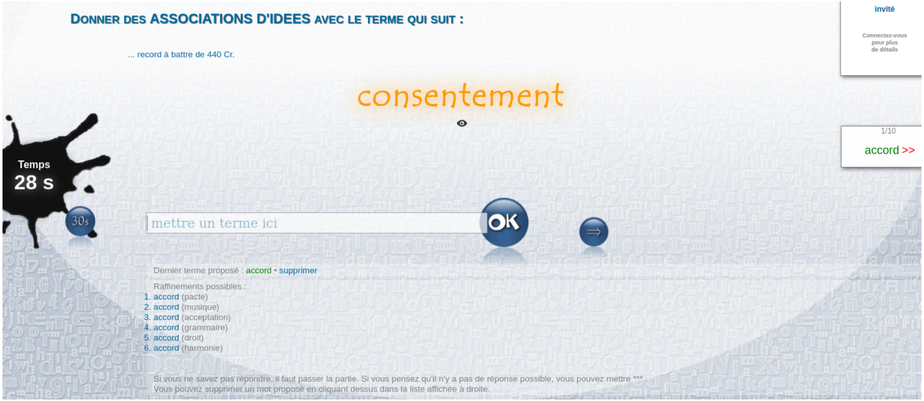

Réseau lexical du français (RL-fr) [Lux-Pogodalla and Polguère, 2011]

- 29,220 nodes and 72,054 edges
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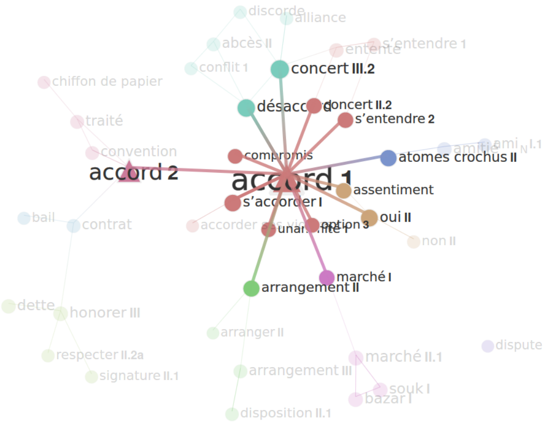

Datasets for French Link Prediction

- `RezoJDM16k` [Mirzapour et al., 2022] and `RLF27k`
- Transductive Link Prediction configuration
- Division into 80%, 10%, 10%

	`RezoJDM16k`	`RLF27k`
# nodes	15,746	27,068
# edges	832,093	71,017
# triples Train	665,674	57,643
# triples Valid	83,209	6,674
# triples Test	83,210	6,700

Metrics based on predictions' scores

- MR (Mean Rank): average rank of the positive triples
- MRR (Mean Reciprocal Rank): average of the reciprocal of ranks of the positive triples
- Hits@k: proportion of positive triples in the top k ranked triples

Training Link Prediction models on RezoJDM16k and RLF27k

Model (For RezoJDM16k)	**MRR ↑**	**MR ↓**	**Hits@10 ↑**	**Hits@3 ↑**	**Hits@1 ↑**
TransE [Bordes et al., 2013]	0.180	200.78	0.437	0.242	0.040
TransH [Wang et al., 2014]	0.217	173.28	0.503	0.293	0.064
TransD [Ji et al., 2015]	0.216	**168.18**	0.500	0.290	0.065
DistMult [Yang et al., 2015]	0.219	194.16	0.446	0.252	0.109
ComplEx [Trouillon et al., 2016]	0.256	190.79	0.539	0.309	0.119
RotatE [Sun et al., 2019]	0.312	177.04	0.587	0.409	0.155
CompGCN-ConvE [Vashishth et al., 2020]	**0.461**	171.26	**0.659**	**0.514**	**0.357**

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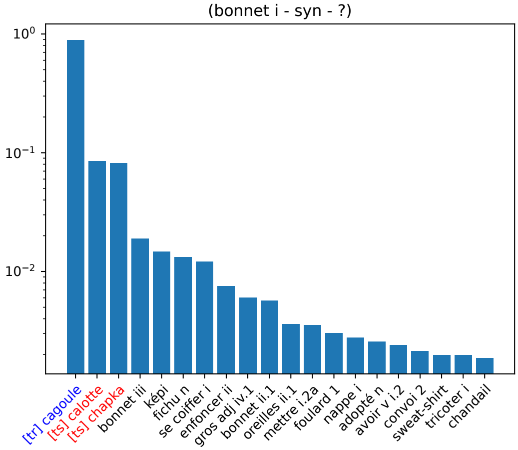
Model (For RLF27k)	**MRR ↑**	**MR ↓**	**Hits@10 ↑**	**Hits@3 ↑**	**Hits@1 ↑**
TransE [Bordes et al., 2013]	0.278	**2594.24**	0.624	0.497	0.033
TransH [Wang et al., 2014]	0.250	2957.59	0.581	0.465	0.011
TransD [Ji et al., 2015]	0.255	2752.03	0.587	0.472	0.016
DistMult [Yang et al., 2015]	0.373	2748.25	0.613	0.502	0.216
ComplEx [Trouillon et al., 2016]	0.413	3447.98	0.593	0.524	0.284
RotatE [Sun et al., 2019]	0.399	3650.92	0.490	0.454	0.336
CompGCN-ConvE [Vashishth et al., 2020]	**0.515**	2808.68	**0.627**	**0.559**	**0.450**

Analyzing CompGCN-ConvE model's predictions



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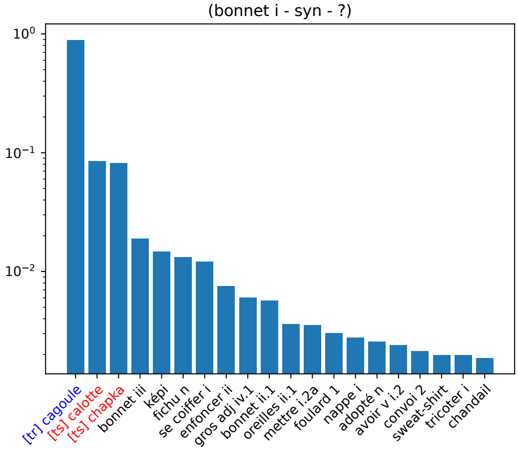

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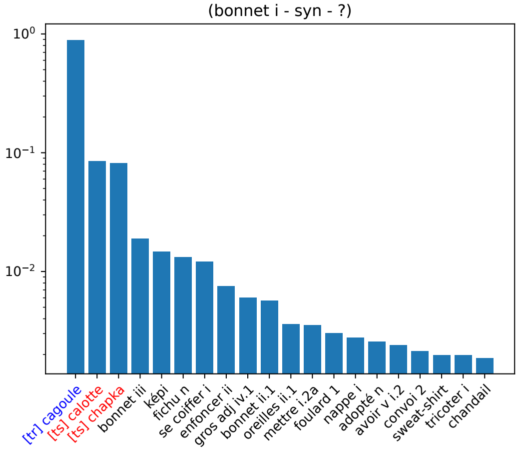

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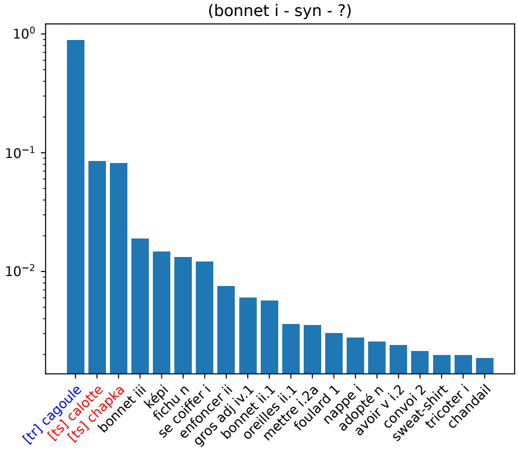

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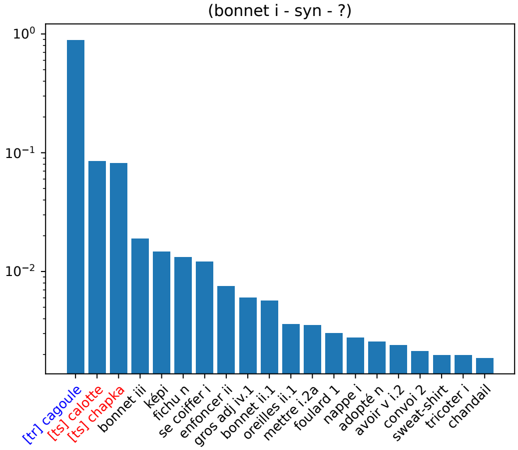

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$\rightarrow$ Function score only can't discriminate relevant new triples

Computing a confidence score with Monte Carlo Dropout

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- Dropout: **Randomly switching off neurons** in a neural network
- **100 output distributions** for the same input by sampling **different dropout mask**
- We compute **how many times a prediction appears in the top 10**.
  Example: If it appears 60 times in the top 10, the confidence score is 60%.

Extracting candidates triples

- We compute the confidence score for all possible combinations of triples for `RezoJDM16k` and `RLF27k`.

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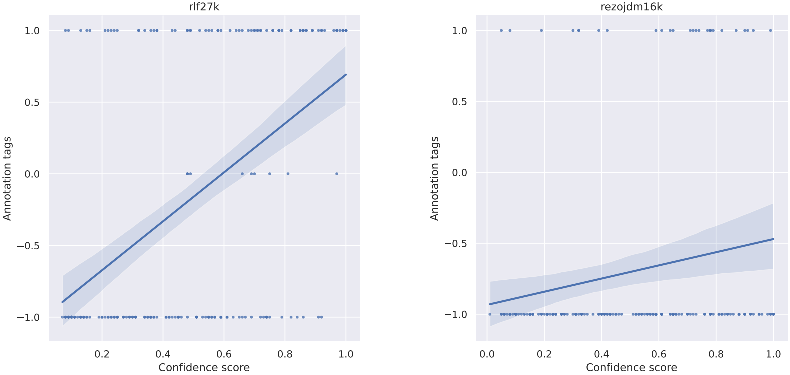
- Triples already existing in the graphs are removed.
- For `RLF27K`, we extract **triples whose entities are not linked by an oriented path** in the graph: 95,766 triples.
- For `RezoJDM16k`, we extract **triples whose entities are furthest apart** (maximum path size 3 and 4): 154,168 triples.

Evaluating confidence score with manual annotations

Annotation of 240 triples by 4 annotators for each dataset.
The task is to determine if two entities are linked with semantic or syntactic relation.
Three annotation tags are used:

- 1: there is a link between the entities
- -1: there is no link
- 0: the link is ambiguous or questionable

Correlation between annotations and confidence scores



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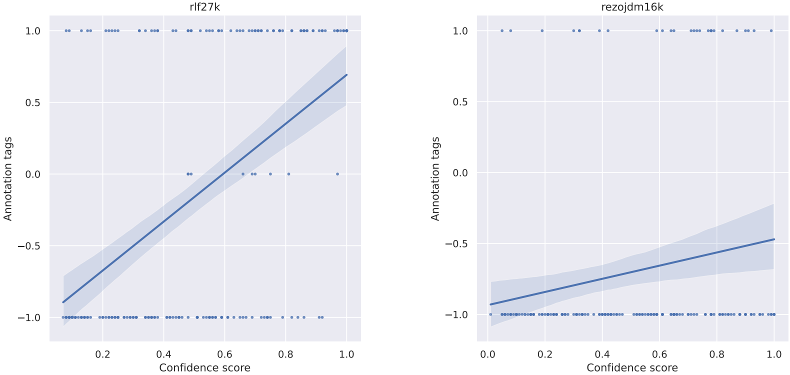

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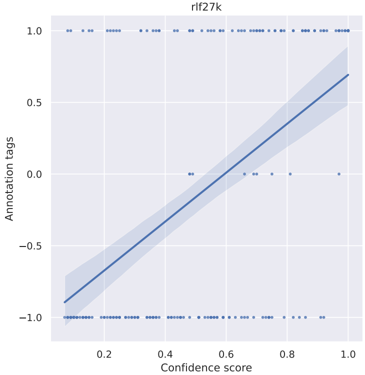
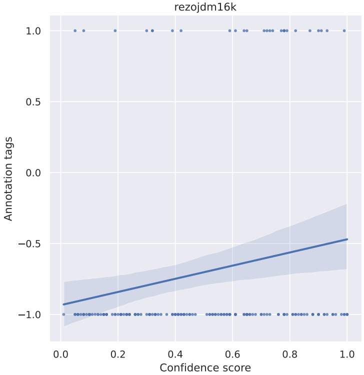
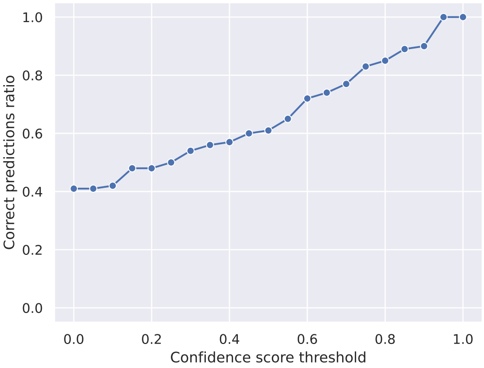




- `RLF27k`: high correlation - triples with high confidence score are relevant
- `RezoJDM16k`: poor correlation due to high density of the graph, two nodes semantically different are related with a relatively short path

Determining a confidence score threshold for RLF27k



→ A confidence threshold of 0.95 results in 100% of triples annotated as correct in RLF27k, which gives us **398 potential good triples** out of the 95,766 candidates.

Relevant new triples for `RLF27k`

- `(kidnappeur, Syn, ravisseur I)` *(kidnapper, Syn, abductor I)*
- `(marchande, Syn, débitante)` *(merchant, Syn, retailer)*
- `(motocycliste n-fem, Syn, motarde)` *(motorcyclist n-fem, Syn, biker)*

Refined triples in RezoJDM16k

- 31% of the edges in RezoJDM16k are the general relation associated

In RezoJDM16k	In CompGCN-ConVE's predictions
(infirmière, associated, personne)	(infirmière, is_a, personne)
(herpès, associated, médecine)	(herpès, domain, médecine)
(ouvrir, associated, fermer)	(ouvrir, antonym, fermer)

Conclusion

Contributions:

- Link prediction on 2 French lexical semantic graphs with 7 models
- Addition of a confidence score to CompGCN-ConvE model's predictions
- Qualitative analysis of predictions based on manual annotations
- Extraction of new triples in `RL-fr`

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Limitations:

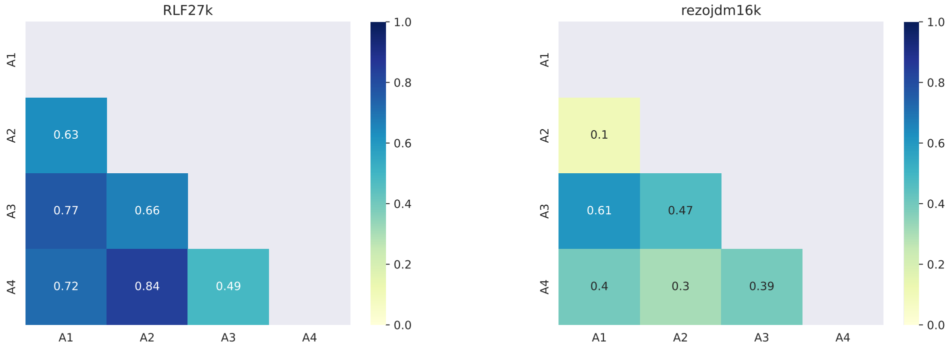
- Need for manual verification of candidate triples
- Influence of the representation of polysemy in different nodes in the `RL-fr`

Work in progress...

- Integrating graph embeddings trained in Link Prediction into EWISER model [Bevilacqua and Navigli, 2020]
- Testing on RL-fr lexicographical examples [Sinha et al., 2022]
- Leveraging supersenses to generate semi-automatically WSD annotations on `fr-SemCor` [Barque et al., 2020] with AMuSE-WSD [Orlando et al., 2021]

Thank you for your attention
Questions?

Inter-annotators agreements



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