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?

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Mathieu Constant, Karën Fort, Bruno Guillaume

LREC-COLING 2024, Turin, Italy

Motivations

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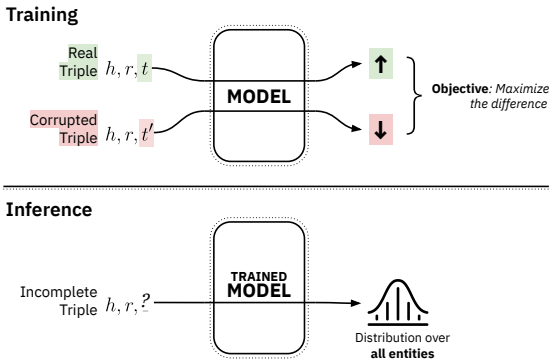
We propose:

- 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.



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- Very dense resource: 6 million nodes and 537 million edges in October 2023
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- Created manually and based on the Meaning-Text Theory [Mel'čuk, 1996]

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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

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! Function score only can't discriminate relevant new triples

Computing a con dence score with Monte Carlo Dropout

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- Dropout: Randomly switching o neurons in a neural network
- 100 output distributions for the same input by sampling di erent 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 con dence score is 60%.

Extracting candidates triples

- We compute the con dence score for all possible combinations of triples for RezoJDM16k and RLF27k.

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- 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 con dence 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

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- RLF27k: high correlation - triples with high con dence score are relevant
- RezoJDM16k: poor correlation due to high density of the graph, two nodes semantically di erent are related with a relatively short path

Determining a con dence score threshold for RLF27k

- A con dence 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 DLF27k

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

Re ned triples in RezoJDM16k

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

In RezoJDM16k	In CompGCN-ConvE 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 con dence 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 veri cation of candidate triples
- In uence of the representation of polysemy in di erent nodes in 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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