Acknowledgements: This work was supported by FCT through the fellowship 2024.01208.BD, and the LASIGE Research Unit, ref. UID/00408/2025. It was also partially supported by the KATY project which has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No 101017453.

Neuro-Symbolic AI for learning over Knowledge Graphs with contradictions

Laura Balbi

LASIGE, Faculdade de Ciências, Universidade de Lisboa, Portugal

Check our paper!

1 Motivation

Knowledge Graphs (KGs) often contain contradictions that are not necessarily errors — they can represent polyvocal truths or nuanced realities that, if properly modeled, can enhance the completeness and expressiveness of KG-based machine learning.

< Jerusalem, wiki:country, Palestine > disputed by Israel, Unites States

< Jerusalem, wiki:country, Israel > disputed by Palestine, United Nations

Wikidata entry Jerusalem (Q1218)

Current KG Representation Learning is not well-equipped to handle contradictory facts within KGs, especially those that are implicit and context-dependent. There is a lack of mechanisms to explicitly model or leverage contradictions during learning.

Taxonomy of Contradictions

Explicit: Logic-based conflicts that can be detected via rule violations or ontology constraints.

Implicit: Conflicting or context-sensitive facts that do not violate formal logic but may be contradictory under additional assumptions or external knowledge.

2 Hypothesis

An approach that integrates symbolic and sub-symbolic representations can bridge KGs and LLMs to answer:

- **RQ1:** How do contradictions in a KG, implicit and explicit, impact the SOTA KGRL performance for PPIs?
- **RQ2:** Does modeling contradictions onto protein representations improve ML?
- **RQ3:** Can external sources of knowledge such as LLMs be explored to detect implicit contradictions?

3 Challenges

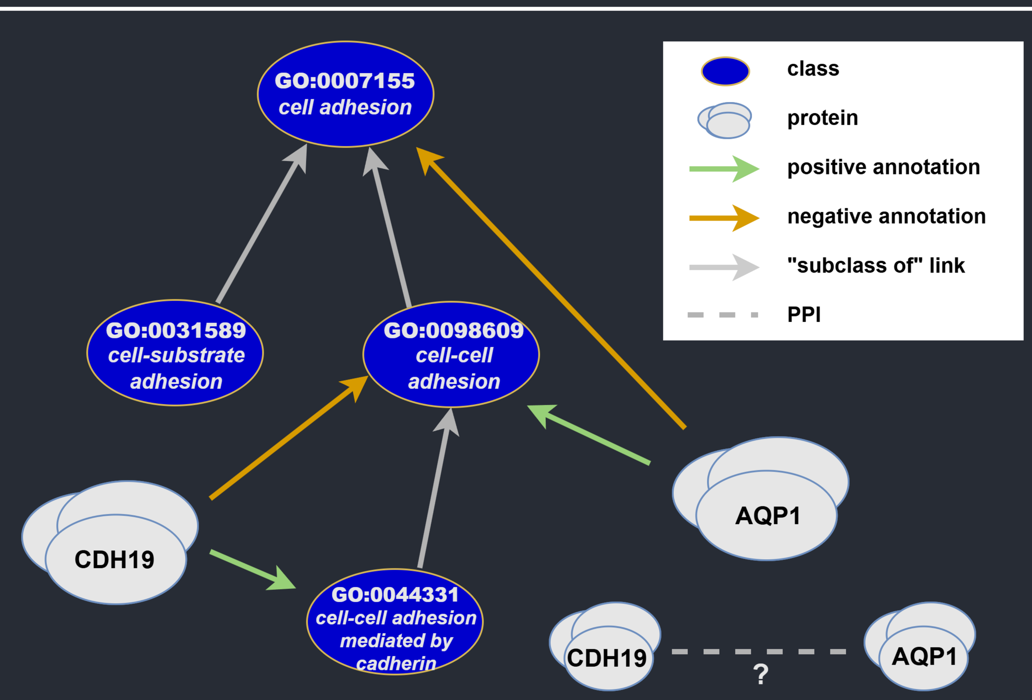
(1) Learning from contradictory statements and particularly with negation must account for:
→ Inheritance
→ Graph closeness ≠ Similarity

(2) Not all contradictions are explicit and some are context dependent

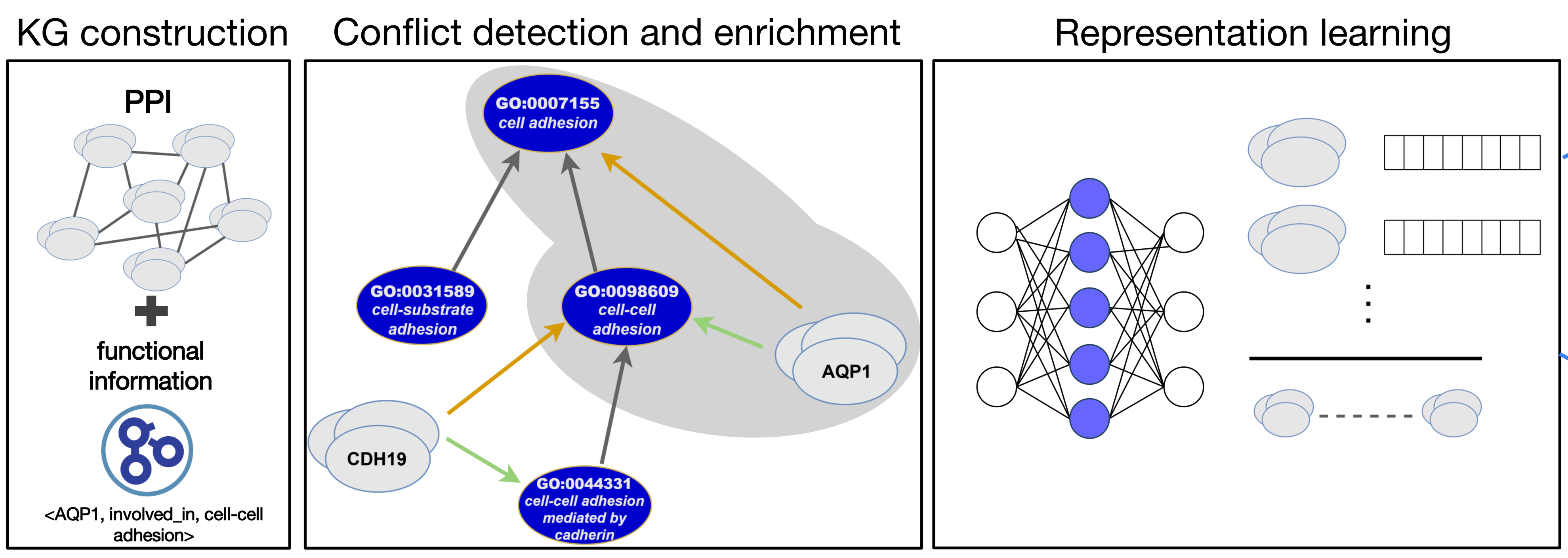
rule-based reasoners symbolic + sub-symbolic

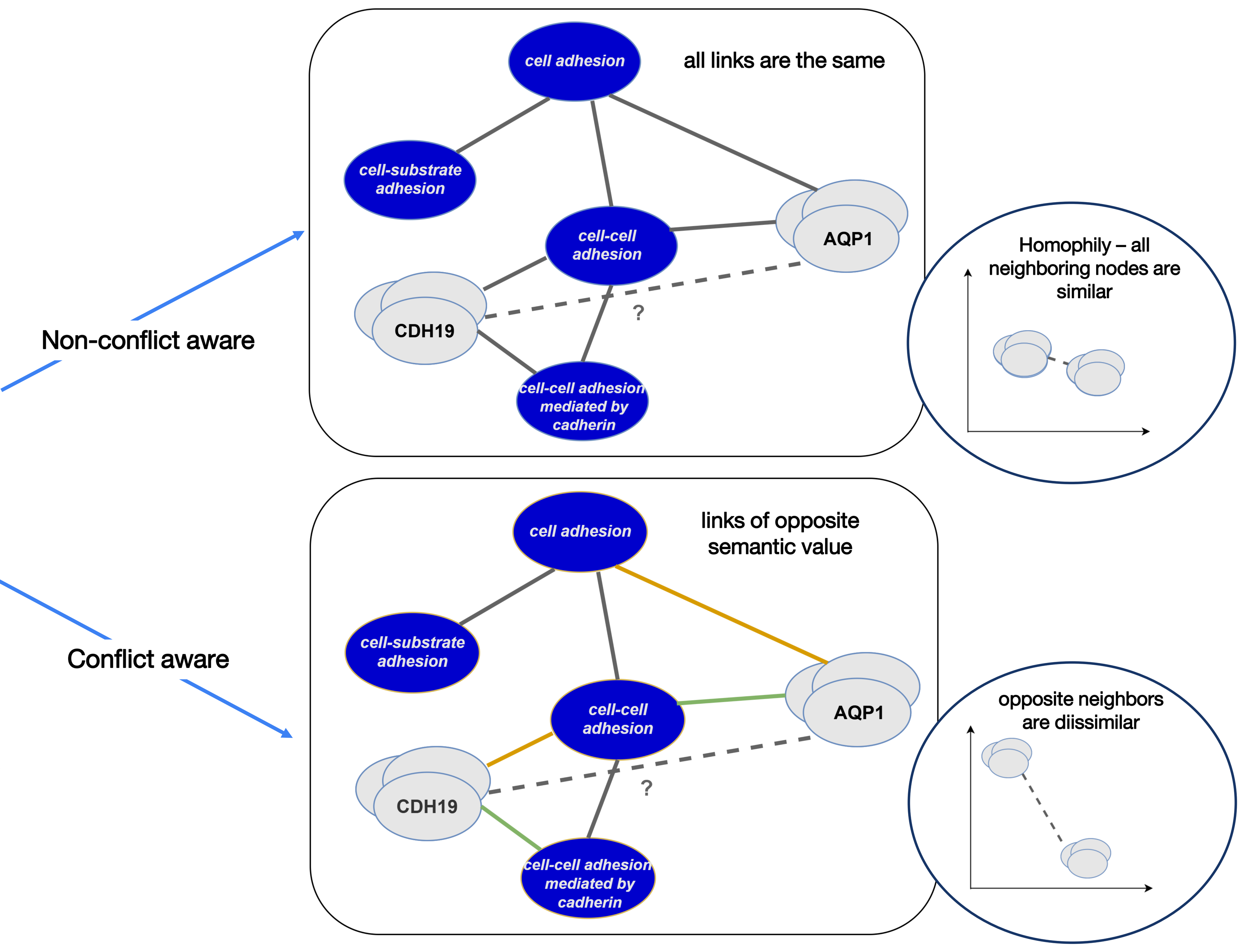
Preliminary focus on modeling contradictions stemming from negation:

- Biomedical use-case (Protein-Protein Interaction prediction)
- KG constructed from Protein-Protein Interaction data and positive and negative statements on protein function aspects (Gene Ontology).



3 Methodology





4 Preliminary experiments

GNN	KG	Acc.	F1	Prec.	Rec.	ROC-AUC
GCN	Full	0.6502	0.6071	0.9440	0.3193	**0.9023**
	w/o contra.	0.6484	0.6041	0.9444	0.3153	0.8998
	Negatives	**0.6567**	**0.6175**	0.9346	**0.3369**	0.8954
	Positives	0.6438	0.5970	**0.9477**	0.3045	0.9007
BiGCN	Full	0.6107	0.5451	**0.9574**	0.2316	0.9002
	w/o contra.	0.6275	0.5719	0.9546	0.2675	0.8976
	Negatives	0.6342	0.5840	0.9391	0.2869	0.8909
	Positives	**0.6540**	**0.6121**	0.9475	**0.3259**	**0.9010**
HGCN	Full	0.6656	0.6294	0.9402	0.3536	**0.8916**
	w/o contra.	**0.6808**	**0.6501**	**0.9441**	**0.3844**	0.8888
	Negatives	0.6704	0.6358	0.9398	0.3640	0.8904
	Positives	0.6732	0.6396	0.9429	0.3687	0.8912

GNN	KG	Acc.	F1	Prec.	Rec.	ROC-AUC
GAT	Full	**0.5721**	0.4795	0.9375	0.1546	**0.6913**
	w/o contra.	0.5690	0.4760	0.9310	0.1491	0.6778
	Negatives	0.6002	**0.5287**	0.9269	**0.2175**	0.6777
	Positives	0.5672	0.4693	**0.9487**	0.1419	0.6888
BiGAT	Full	0.5673	0.4688	0.9452	0.1438	0.6642
	w/o contra.	0.5498	0.4420	0.8853	0.1140	0.6255
	Negatives	**0.5872**	**0.5113**	0.9105	**0.1945**	**0.6990**
	Positives	0.5705	0.4743	**0.9470**	0.1504	0.6636
HGAT	Full	0.5662	0.4702	0.9386	0.1414	**0.7030**
	w/o contra.	0.5661	0.4702	0.9391	0.1415	0.6985
	Negatives	**0.5766**	**0.4891**	0.9393	**0.1639**	0.7021
	Positives	0.5506	0.4386	**0.9599**	0.1057	0.6775

Including contradictions improves performance even if models are not equipped to handle it.

Modeling negative and positive statements separately improves performance.

Potential to increase performance with algorithms that account for contradictions.