

Neuro-Symbolic AI for modelling Bio-Knowledge Graphs with contradictions

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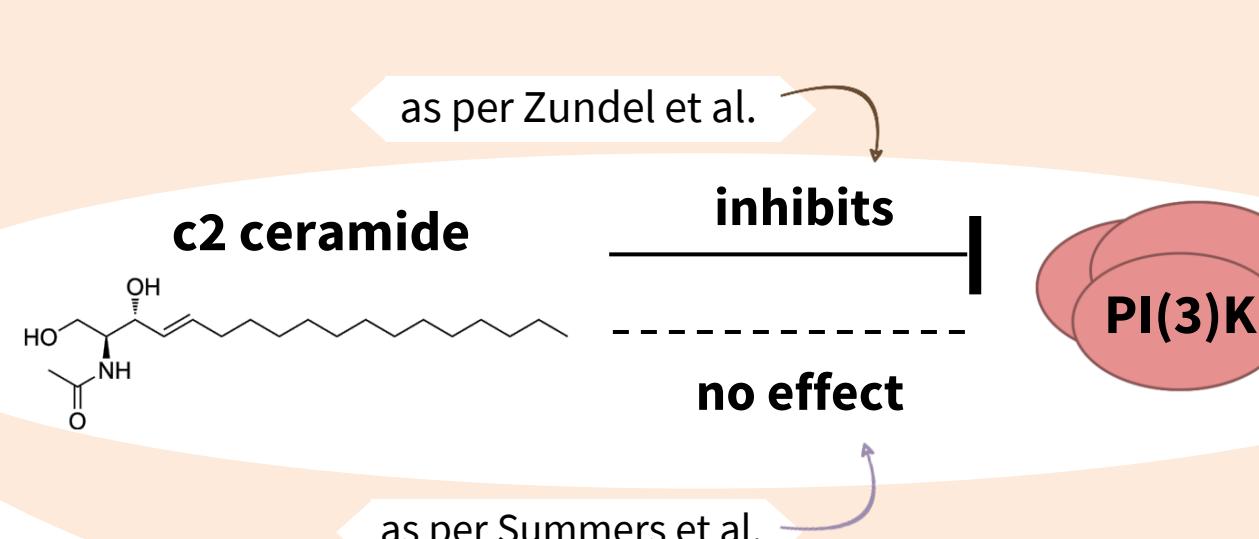
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Motivation

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.

In biomedical KGs this may be due to the universe of experimental conditions in which biological entities perform specific roles, functions and interactions.

In the case of protein interactions with other molecules, we cannot assume that an interaction is always held true



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

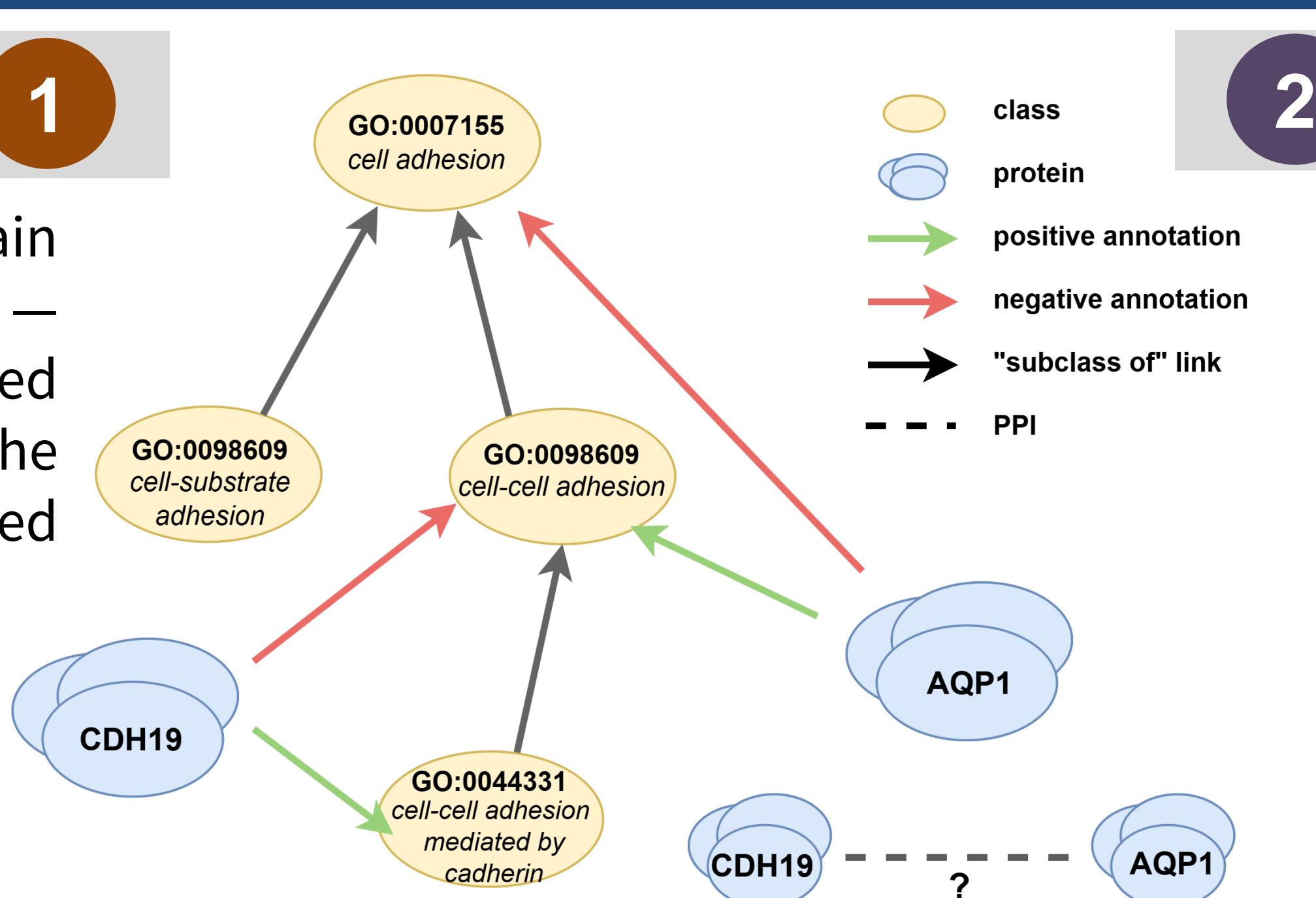
Explicit

Direct, logic-based conflicts that can be detected via rule violations or ontology constraints.

Implicit

Semantically conflicting or context-sensitive facts that do not violate formal logic alone, but appear contradictory under additional assumptions or external knowledge.

Subtype		Description	Example
Direct	Negated Assertion	Presence of both an assertion and its negation.	<ProteinA, interactsWith, ProteinB> AND <ProteinA, NOT interactsWith, ProteinB>
	Disjoint Classes	Assigns an entity to classes that are explicitly declared disjoint.	<TS T53, typeOf, Protein> AND <TS T53, typeOf, Disease> AND Protein ⊥ Disease
Indirect	Inverse Property Conflict	Conflicting values in mutually inverse properties.	<GeneA, encodes, ProteinA> AND <ProteinA, encodedBy, GeneB>
	Cardinality/ Domain/Range Violation	Violation of property constraints.	<ProteinA, hasCatalyticFunction, Kinase> AND <ProteinA, hasCatalyticFunction, Protease> (if hasCatalyticFunction is 1:1)
Hierarchically Inferred		Conflict from inherited logical constraints.	<ProteinA, hasFunction, DNA repair> AND <ProteinA, hasFunction, Negative regulation of DNA repair> AND DNA repair ⊥ Negative regulation of DNA repair

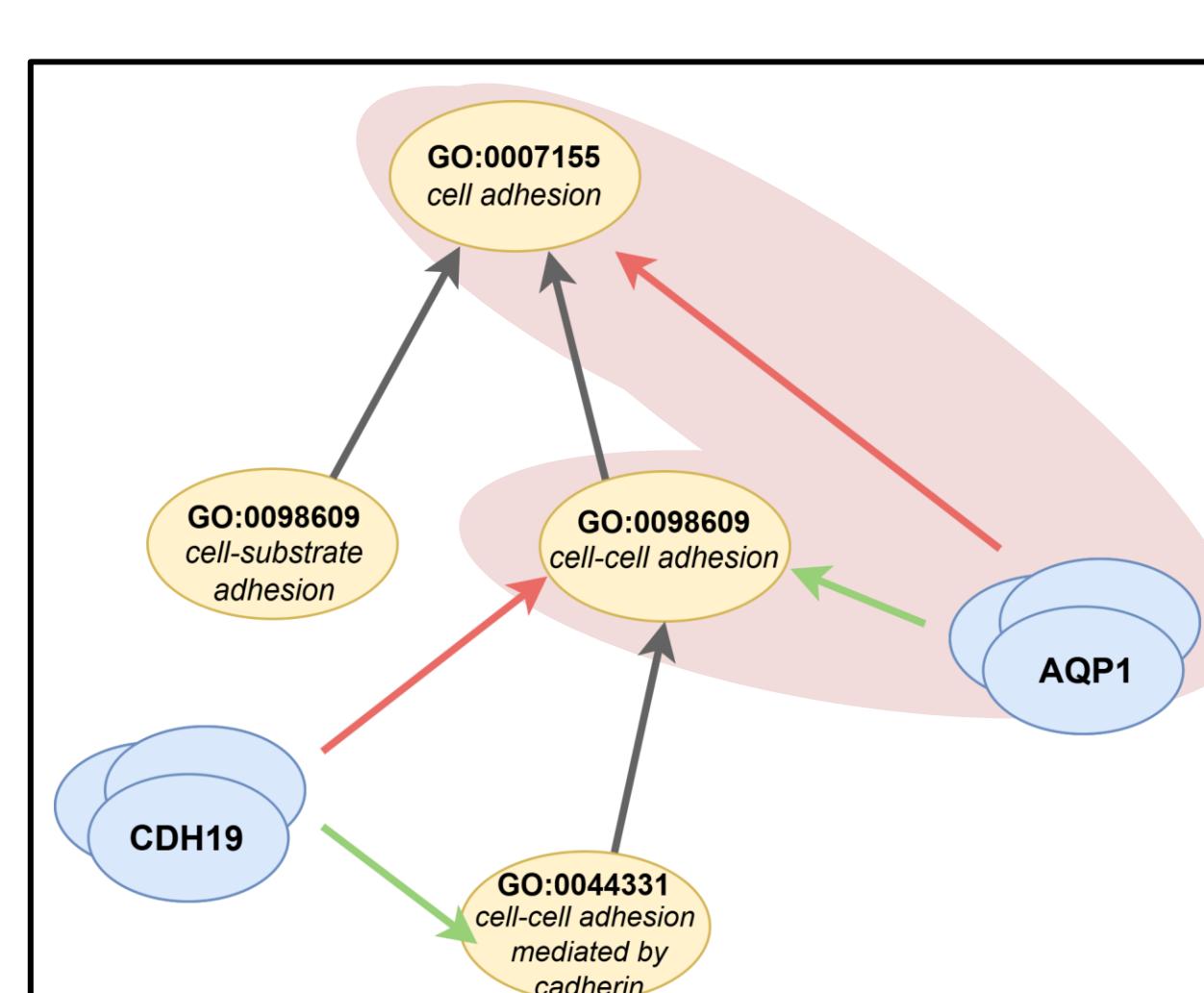
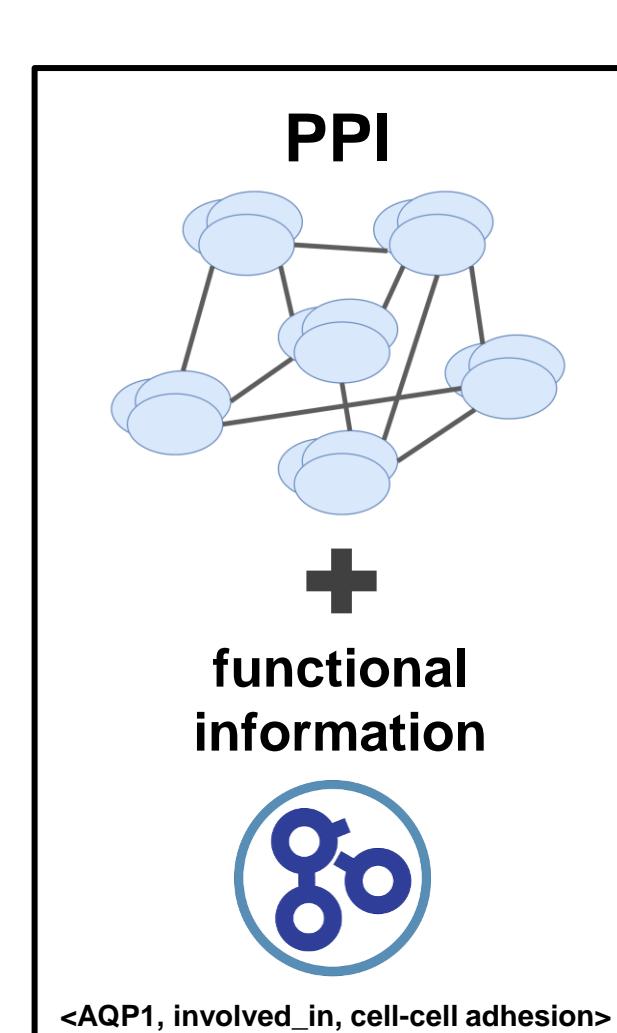


Hypothesis

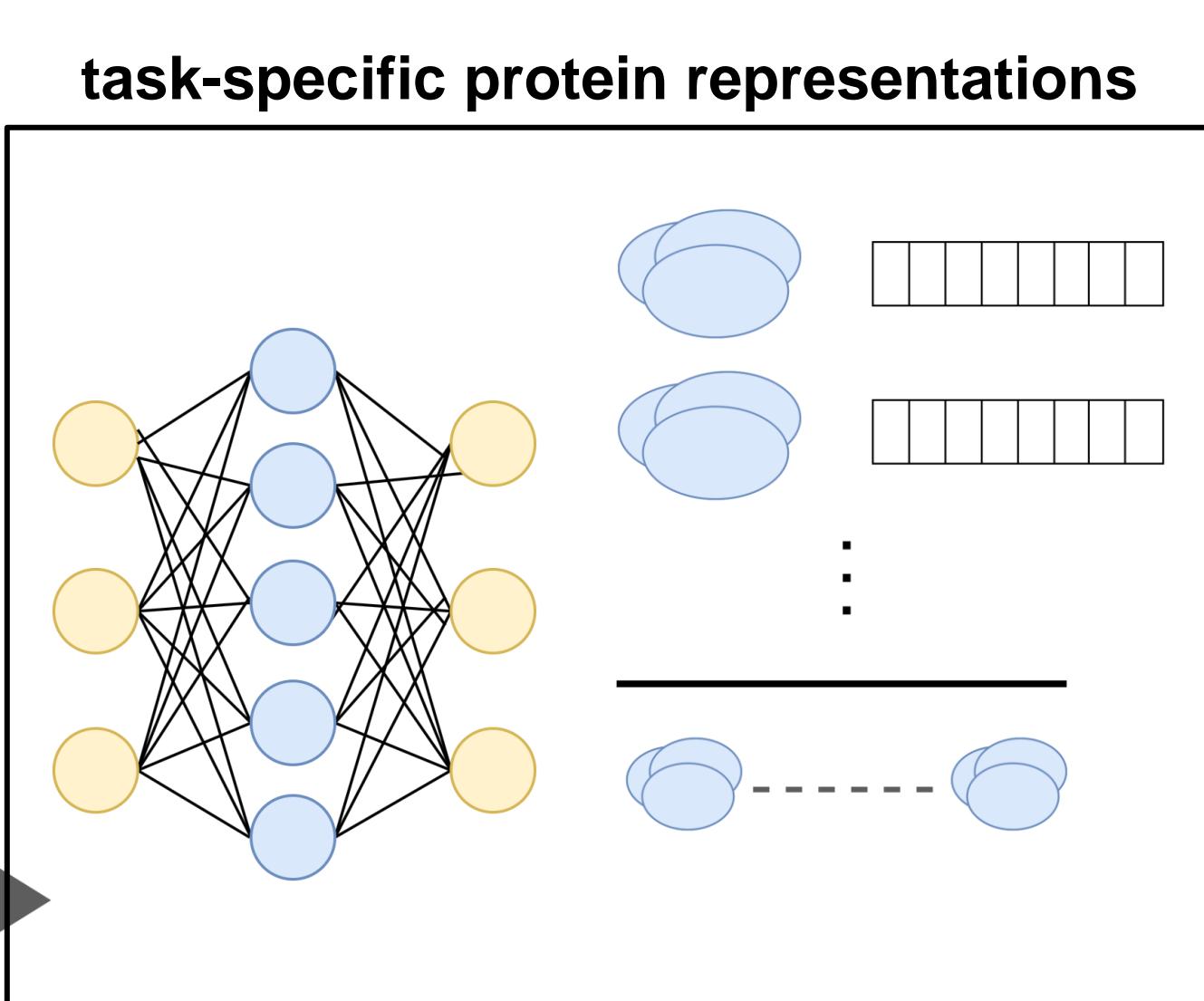
An approach that integrates symbolic and sub-symbolic representations can bridge KGs and LLMs to answer:

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

Methodology



contradiction detection



Baselines

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ML	KG	# Edge Types	Precision	Recall	ROC-AUC
HGNC	Full	1	0.9440	0.3193	0.9023
		2	0.9574	0.2316	0.9002
		5	0.9402	0.3536	0.8916
HGAT	Full	1	0.9444	0.3153	0.8998
		2	0.9546	0.2675	0.8976
		5	0.9441	0.3844	0.8888
HGAT	no LC	1	0.9346	0.3369	0.8954
		1	0.9391	0.2869	0.8909
		4	0.9398	0.3640	0.8904
HGAT	Negative Annots	1	0.9477	0.3045	0.9007
		2	0.9475	0.3259	0.9010
		4	0.9429	0.3687	0.8912
HGAT	Positive Annots	1	0.9375	0.1546	0.6913
		2	0.9452	0.1438	0.6642
		5	0.9386	0.1414	0.7030
HGAT	no LC	1	0.9310	0.1491	0.6778
		2	0.8853	0.1140	0.6255
		5	0.9391	0.1415	0.6985
HGAT	Negative Annots	1	0.9269	0.2175	0.6777
		1	0.9105	0.1945	0.6990
		4	0.9393	0.1639	0.7021
HGAT	Positive Annots	1	0.9487	0.1419	0.6888
		2	0.9470	0.1504	0.6636
		4	0.9599	0.1057	0.6775

Preliminary discussion

value of including negative knowledge
only negative annotations outperform

advantage in actively modelling opposing relations and contradictions in separate
consensual increase in performance from the
GCN to the HGCN

GAT weighs edges according to their
importance across edge types

GAT overperformed
Bi- and HGAT

