

# Knowledge Graphs can play together: Addressing knowledge graph alignment from ontologies in the biomedical domain

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#### **Problem Statement**

- Construct a generalized domain-specific knowledge graph from domain text and ontological sources
- Leverage domain-specific vocabulary to find patterns in different domain texts
- Domain of application: Pharmaceuticals
- RQ1: Can domain ontological sources be leveraged as a basis for constructing a knowledge graph from unstructured text?
- RQ2: Can domain ontological sources be used to align knowledge graphs from different sources?









#### **DomainKnowledge Pipeline Overview**

 Leverages document parsing, entity-relation triple extraction and knowledge graph construction modules



# **DomainKnowledge Modules – Annotator**

- Module to extract triples from document text based on relevant domain entities
- Triples of the form (subject, relation, object)
- Subject and object entities should be relevant to the domain (e.g., Pharmaceuticals)
- Relations of 2 types:
  - Verbal: relations containing verb as a cornerstone
  - Prepositional: relations built from adpositions (e.g., as, with, for)
- Additional document metadata extracted









- Integrates domain ontologies to validate and ground extracted triples from text
- Relies on UMLS tables
- Table ontologies re-organized into one consolidated knowledge graph based on ontological information for nodes and relations
- AUI, CUI, LUI, SUI and TUI nodes included in knowledge graph construction
- Node relations created to bind ontological nodes hierarchically





- AUI: atom
- CUI: concept
- LUI: term
- SUI: unique string

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TUI: semantic type

• CUI node has an atom node: 
$$CUI \xrightarrow{HAS\_AUI} AUI$$

• SUI node has an atom node: 
$$SUI \xrightarrow{HAS\_AUI} AUI$$

• SUI node has concept node:  $SUI \xrightarrow{HAS\_CUI} CUI$ 

• CUI node has semantic type node:  $CUI \xrightarrow{HAS\_STY} TUI$ 



# **DomainKnowledge Modules – Merger**

- Integrates extracted triples into ontology knowledge graph
- Point of entry is SUI node
- Comparison based on 2-step string matching:
  - Exact matching (Levenshtein distance)
  - Semantic matching (cosine score on 512-dimensional vector embeddings)
- Triple entities and relations inserted as nodes (NER) and edges in knowledge graph
  - Text node linked to another text node:  $NER \xrightarrow{TEXT \perp INK} NER$
  - Text node matched to SUI node:  $NER \xrightarrow{HAS\_LEXICAL} SUI$









# **Metrics – Coverage**

- 3 metrics defined to evaluate efficacy and pertinence of final graph
- Some formalization:
  - Domain Tokens (DT) = set of entities from input texts with a direct relation to an ontology node
  - Text Tokens (TT) = set of all extracted entities from input texts
  - Coverage = Percentage of domain vocabulary present in input texts



 $\frac{|DT|}{|TT|} \times 100$ 



(1)



# **Metrics – Mapping**

- Some formalization:
  - Domain Tokens (DT) = set of entities from input texts with a direct relation to an ontology node
  - Concept Tokens (CT) = set of all extracted entities from input texts with same syntactic name as ontology node
  - Mapping = Percentage of entities directly found in the ontology knowledge graph

$$\frac{|CT|}{|DT|} \times 100 \tag{2}$$







# **Metrics – Alignment**

- Some formalization:
  - rNER→TUI = Direct relation from text entity to ontological semantic type
  - rCUI→TUI = Direct relation from concept to ontological semantic type
  - rTUI = Relation from a given source node to an ontological semantic type
  - We define:  $rTUI = rNER \rightarrow TUI + rCUI \rightarrow TUI$
  - Alignment = Overlap score between text entities and ontological semantic types

$$\frac{count(r_{NER} \rightarrow TUI)}{count(r_{TUI})} \times 100$$
(3)

# **Experimental Setup**

- 2 experiments conducted on 52 Clinical Study Reports (CSR) documents
- Goal: Finding maximum direct relations between NER and CUI/TUI nodes
- Experiment 1:
  - Group sentences based on sentence scores
  - Extract and consolidate relevant NER and CUI/TUI nodes
  - Promising but computationally heavy
- Experiment 2:
  - Calculate node importance score for NER and ontological nodes
  - Assign weights to relations between nodes based on cumulative node importance scores
  - Graph traversal algorithm to find the maximum total weight between NER and TUI source and target nodes







### Results

- Evaluation done against human baseline with domain experts (Clinical Analysts)
- DomainKnowledge beats human baseline in all metrics
- Alignment score weak possibility to improve by enriching domain ontologies
- Gap in score between metrics highlights difficulty in alignment

Method	CVRG	MAPG	ALGT
Baseline	68.00	40.00	10.00
Our Pipeline	76.16	53.67	21.40

Table 3: Comparative results of our methodology.









# Conclusion

- Initial results on domain show promise
- RQ1: Can domain ontological sources be leveraged as a basis for constructing a knowledge graph from unstructured text? Ontologies are key to constructing structured knowledge graphs from unstructured sources
- RQ2: Can domain ontological sources be used to align knowledge graphs from different sources? Metrics play an important role in measuring alignment in addition to the right ontological sources
- Alignment remains a hard problem
- Work lays groundwork for extended experimentation on more domains









#### Thank You

#### Questions







