Understanding KGs

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Knowledge Graphs: Data Graphs

Takeaways

- Graph models store connections between data points, making them ideal for representing relationships.
- Different graph models (directed edge-labeled, property graphs, etc.) serve different use cases and complexity levels.
- Graph patterns act like templates to match and extract specific subgraphs from your data.

Knowledge Graphs: Data Graphs

Takeaways

- Query results can be manipulated using relational operations like projection, selection, and joins.
- Path expressions enable navigation through multiple connections, finding relationships that span several hops.
- Graph databases like Neo4j implement these concepts for real-world applications.

Knowledge Graphs: Data Graphs

Q & A

If KGs can use different graph models, what requirements determine which one to choose?

- **Directed Edge Labelled Graph:** Prioritize strategic logical definition and advanced deductive reasoning by adhering to formal semantics and open W3C standards.[8]
- **Property Graph:** Prioritize tactical analytical speed and high performance for managing big data and complex graph traversal workloads.[8]

Knowledge Graphs: Data Graphs

Q & A

Discuss more on Heterogeneous Graph.

- A **Heterogeneous Graph (HG)**, also known as a **Heterogeneous Information Network (HIN)**, is a specialized network model designed to reflect the non-uniform complexity of real-world data. [9]
- It rigorously defines multiple distinct types of nodes and edges, preserving critical semantics often lost when modeling complex systems. [9]

Knowledge Graphs: Data Graphs

Q & A

Discuss more on Heterogeneous Graph.

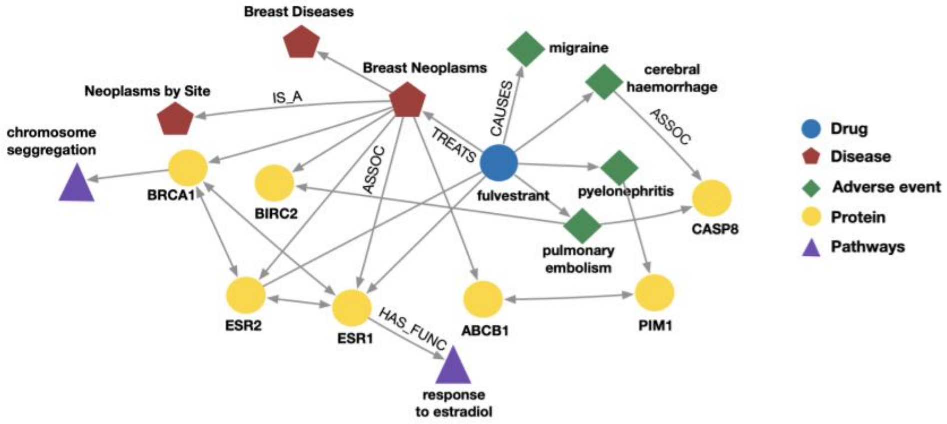


Fig: Example of Heterogeneousneous Graph

Knowledge Graphs: Data Graphs

Q & A

In what way does the modern KG integrate the best aspects of existing models?

- **Logical Backbone (RDF):** Use the RDF model to enforce definitive facts, standards, and deep logical reasoning. [8]
- **Speed and Analytics (Property Graph):** Use the Property Graph model for high-speed performance on analytical queries and graph traversals. [8]
- **AI/ML Focus (Heterogeneous Graph):** Integrate specialized Heterogeneous Graph structures when modeling complex, multi-typed relationships necessary for advanced AI applications. [9]

Knowledge Graphs: Schema, Identity, Context

Takeaways

- **Shapes** are used to define a **validation graph**. These shapes are a set of nodes that have been selected for specific constraints.
- **Semantics**, **validation**, and **emergent schemata** together support reasoning, constraint validation, and automatic structure discovery within knowledge graphs.
- **Lexicalisation** through the use of **identifiers** with labels is a great way to ground a nodes identity and allow for cross referencing in other texts.

Knowledge Graphs: Schema, Identity, Context

Takeaways

- When representing data of many varieties on larger scales the default choice in semantic representation is **OWA**.
- Contextual information scoping like **provenance** and **temporal scope** complements schema and identity to ensure that knowledge remains meaningful and accurate across different context specific situations

Knowledge Graphs: Schema, Identity, Context

Q & A

What are the similarities and differences between reification and Higher-arity representation?

- **Reification**: Making statements about statements. Useful for including provenance data about a thing. The Statement becomes a node [2, 3]. Used for a single triple.

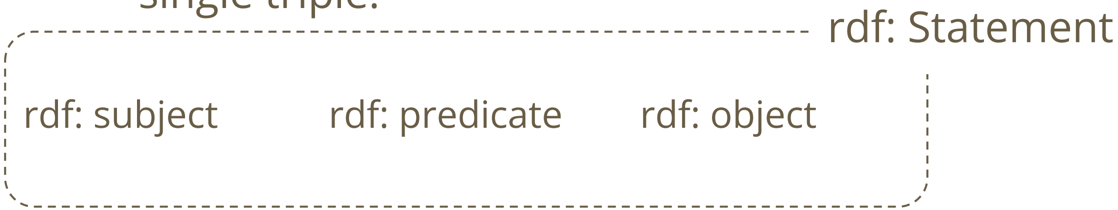


Fig1: A simple example of what can be contained within an rdf: Statement.

```
:statement1 a rdf: Statement ;
        rdf: subject      :Subject ;
        rdf: predicate  :Predicate ;
        rdf: object       :Object ;
:statement1 :statedBy :Person1 .
```

Fig2: How a reification would look in TTL.

Knowledge Graphs: Schema, Identity, Context

Q & A

What are the similarities and differences between reification and Higher-arity representation?

- **Higher-arity**: Making a statement about statements, but for an entire graph. These graphs can be either subjects or objects of RDF triples [1, 2, 3].

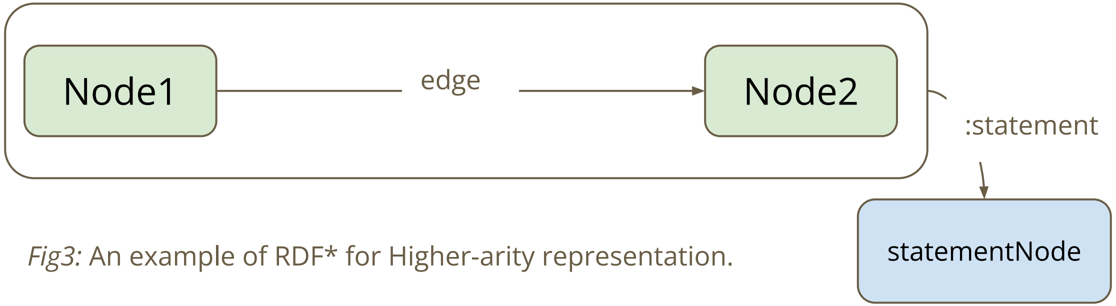


Fig3: An example of RDF* for Higher-arity representation.

```
<< :node1 :edge :node2 >> :statement :statementNode .
```

Fig4: How a RDF* statement would look in TTL.

Knowledge Graphs: Schema, Identity, Context

Q & A

What are the differences between open and closed world assumptions?

- CWA:
  - Anything unknown is false.
  - In other words, if a **fact** does not exist in the **KB**, then it false [3].
- OWA:
  - Anything unknown is simply that and is **NOT** assumed to be false [3].

Knowledge Graphs: Schema, Identity, Context

Q & A

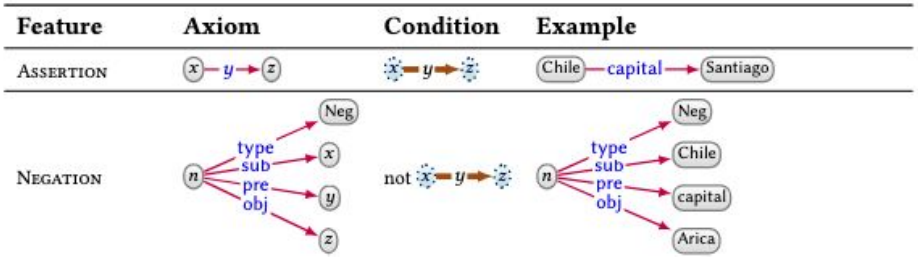
Can you more clearly define a quotient graph?

- A **quotient graph** is a summary of a **data graph** which shows the high level structure by merging (**partitioning**) nodes from the original data graph based on an equivalent relationship [3].

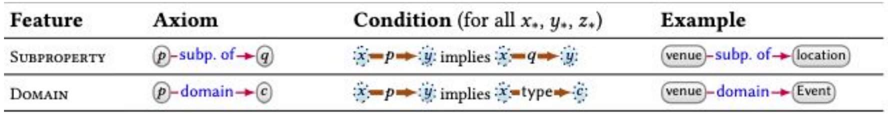
Knowledge Graphs: Deductive Knowledge

Takeaways

- **<u>Q: Can machines deduce new knowledge from a data graph?</u>**
- Machines can "deduce" by producing conclusions from a set of premises (*entailment regimes*)
- Machines require
  - *ontologies* (a schema of knowledge that can be mapped to a graph)
  - *rules for interpretations* (ways to understand the data in the context of the real world)



Feature	Axiom	Condition	Example
Assertion	x — y → z	x — y → z	Chile — capital → Santiago
Negation	n —type→ Neg; n —sub→ x; n —pre→ y; n —obj→ z	not x — y → z	n —type→ Neg; n —sub→ Chile; n —pre→ capital; n —obj→ Arica



Feature	Axiom	Condition (for all x_*, y_*, z_*)	Example
Subproperty	p — subp. of → q	x — p → y implies x — q → y	venue — subp. of → location
Domain	p — domain → c	x — p → y implies x — type → c	venue — domain → Event

Figures: Relationships between axioms (properties) and semantic conditions (meanings) from Hogan et al.

Knowledge Graphs: Deductive Knowledge

Takeaways

- **Semantic conditions** allow for *entailments* on graphs
- Whether one graph can be entailed by another is an *undecidable problem* – approx. solutions below:
  - Sol 1: halt on any input ontology but miss entailments
  - Sol 2: always halt on restricted feature ontologies
  - Sol 3: Only return correct answers for an ontology, but may never halt on certain inputs
- There are two approaches to entailment:
  - Adding If-Then/If-Then-Else conditional Rules
  - Using Description Logics to assert axioms about individuals, classes (groups/concepts) and properties (roles)

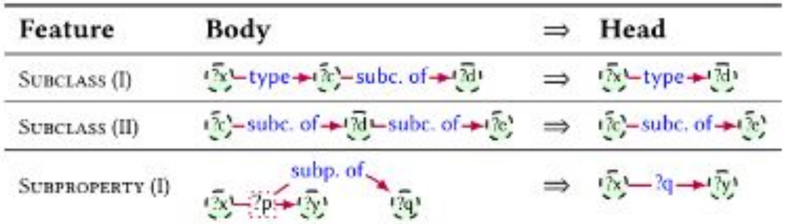


Figure: Example of IF-THEN rules for specific properties: IF (body) THEN (head), from Hogan et al.

Knowledge Graphs: Deductive Knowledge

Q & A

What is meant by "Expressive Deduction Logics" in the last paragraph on page 32?

- *Expressive* in that context refers to DLs that have different constructs which can "express" or capture certain properties better. Some general examples below, from [4]:
  - SROIQ is a well-known DL with certain axiomatic and constructor restrictions
  - ALC is a more restricted SROIQ-based DL, which lacks even more axioms and has more constraints
  - EL is another DL family that has unlimited existential quantifiers
- These DLs allow us to capture certain relationships, but have tradeoffs on computability and decidability

Knowledge Graphs: Deductive Knowledge

Q & A

How can we balance between more expressive ontologies – which allow richer reasoning – and computational tractability in real-world?

- Ultimately, this comes down to the use case and the reasoners we use.
- Do we want
  - fast entailments which are generally correct,
  - entailments that are always correct but very slow to calculate, etc...
- Hogan et al. state: "[the option of always getting the correct entailment]... only accept[ing] [restricted] input ontologies... may be a better choice in [medical] domains... where missing entailments may have undesirable outcomes", as an example

Knowledge Graphs: Deductive Knowledge

Q & A

How do SPARQL Inferencing Notation (SPIN) and Description Logic work for real-world deductive reasoning? Can they work together?

- **One asks (SPARQL), the other describes (DL). Both RDF and DL have query languages and specific semantics, but they aren't immediately compatible.**
- SPARQL is a query language for RDF and OWL ontologies, per [6], and SPIN allows one to express SPARQL queries as RDF triples, per [5].
- DLs, on the other hand, are a different type of ontology modeling language [4], with links to OWL Web Ontology Language. DLs give rise to Direct Semantics, whereas there are RDF semantics (which make reasoning undecidable)
- DLs do have Query Languages, such as DIG protocol and nRQL queries [6], but there is a problem in combining SPARQL/SPIN with OWL-DL-based ontologies, as seen by [6]

<u>Some efforts were made to bridge SPARQL and DL families.</u>

- The authors in [6] try to create a SPARQL-like QL for OWL-DL ontologies
- The paper "Using Description Logics for RDF Constraint Checking and Closed-World Recognition" [7] by Patel-Schneider may provide more details, where DL axioms can be used for constraint checking on RDF graphs, and constraint checking/closed-world recognition can be translated to SPARQL queries.

Knowledge Graphs: Creation and Enrichment

Takeaways

- Ontology engineering as a downstream step
  - Comes after data ingestion and processing to ensure entities, relations, and schemas are structured correct.
- Two modes of ontology creation:
  - Ontology learning (automatic ML/NLP-driven) - scales well but needs careful validation to not introduce errors
  - Human-based construction - provides domain expertise, precision, and curation but expensive

Knowledge Graphs: Creation and Enrichment

Takeaways

- NLP techniques at the core of building and enriching KGs
  - Named Entity Recognition (NER); Entity Linking (EL); Relation Extraction (RE)
- Challenges with entity linking:
  - Ambiguous entities requiring disambiguation using contextual ranking
  - Consistent representation of entities with aliases
- SPARQL for enrichment by filtering subsets
- Validation of ontologies (KGs) with CQs

Knowledge Graphs: Creation and Enrichment

Q & A

How do transformers and ANNs perform at ontology learning from text? What bottlenecks exist?

- Transformers (LLMs) show promise wrt extraction of richer semantics [1] but bottlenecks include lack of domain-specific training data, interpretability, and difficulty in aligning extracted patterns with formal ontologies (Saini et al , 2025 - KGSWC)

Among enrichment methods (human collaboration, text/markup extraction, structured sources, leveraging external KGs), which are most impactful at scale?

- Incremental enrichment with structured sources and external KGs scale resource effective but human based extraction might give better quality in data with formal ontology considerations.

Knowledge Graphs: Creation and Enrichment

Q & A

When validating an ontology/KG with results partially incomplete/inaccurate, what's the troubleshooting order?

- Verify the query with CQ - > Check required data existence in KG - > Check for valid ingestion and materialization - > Revisit ontology design and schema wrt to CQs; Verify Key notions

How has ontology learning been applied in practice?

- [Placeholder]

References

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