

192.161 Management of Graph Data

(4.0 VU / 6.0 ECTS)

2025W

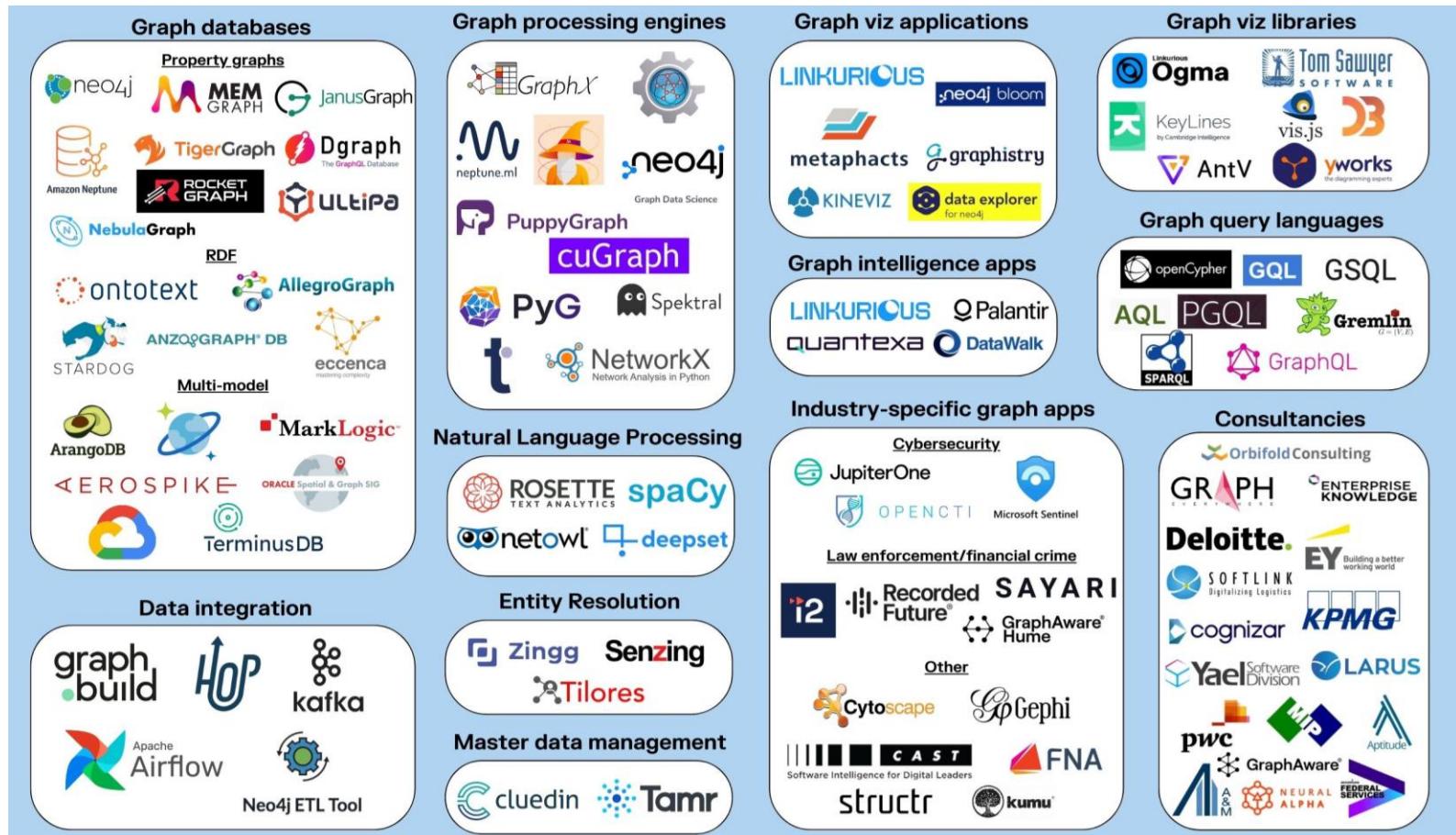
Advanced Topics

**Katja Hose
Maxime Jakubowski**

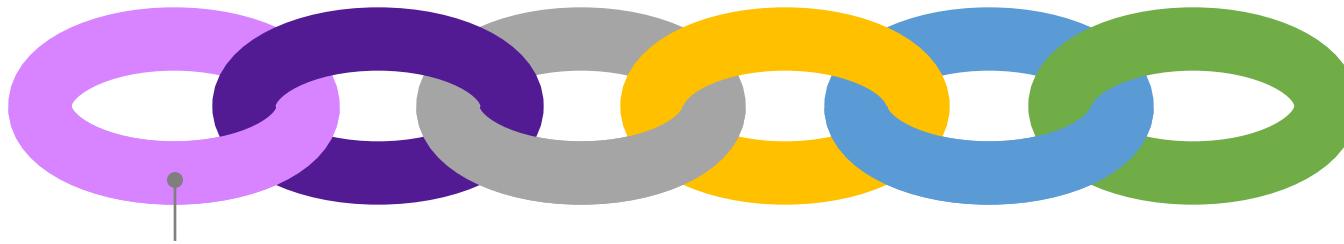
mogda@list.tuwien.ac.at

- Advanced topics in graph data management
- Course feedback
- Exam information

Graph technology landscape



Knowledge graph challenges for GDBMS and AI



Data Modeling and Interoperability



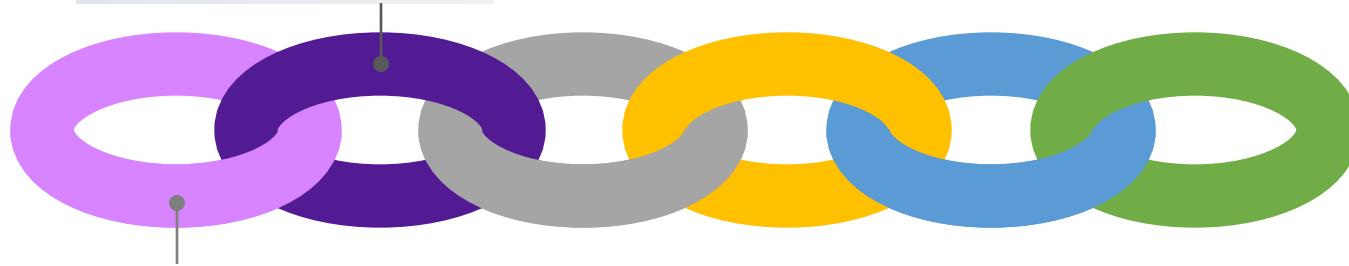
- alternative graph data models (RDF, property graphs) and query languages (SPARQL, Cypher, GQL)
- schema modeling (ontologies, PG-schema)
- multimodal data
- data integration (OBDA, entity resolution, virtual KGs, etc.)

Knowledge graph challenges for GDBMS and AI

Scalability and Querying



- efficiently handling large-scale graphs
- indexing, statistics, query optimization
- centralized/cluster/federated
- example-driven analytics and exploration



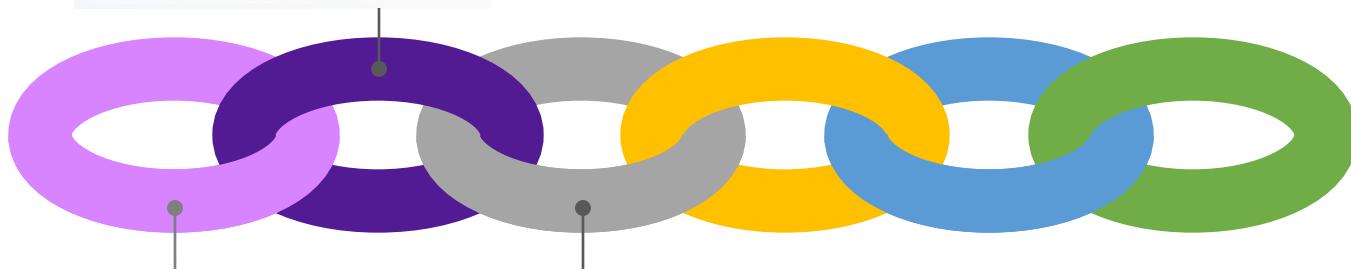
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Data Modeling and Interoperability Quality, Provenance, and Dynamics

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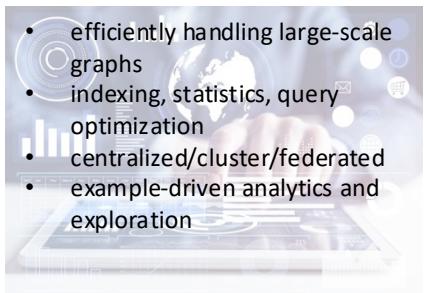


- ensuring accuracy, completeness, and consistency (SHACL, SHeX, PG-schema)
- Knowledge evolution, temporal knowledge graphs
- provenance, lineage

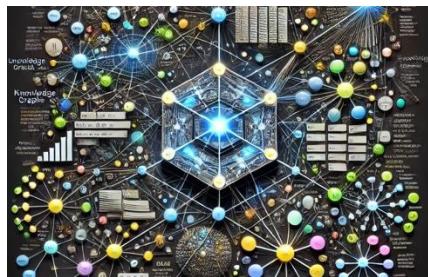
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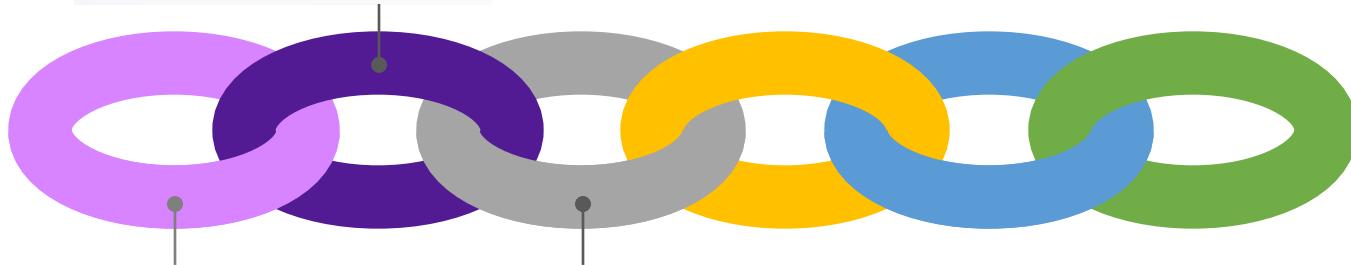
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Reasoning and Neurosymbolic AI

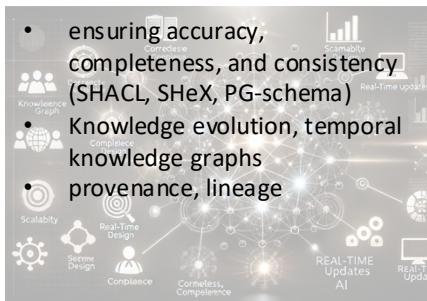
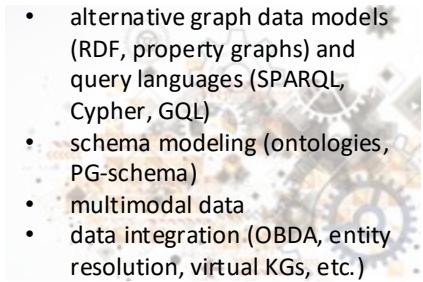


- combining logical reasoning with machine learning embeddings, vector representations
- graph neural networks
- multi-modal ML



Data Modeling and Interoperability Quality, Provenance, and Dynamics

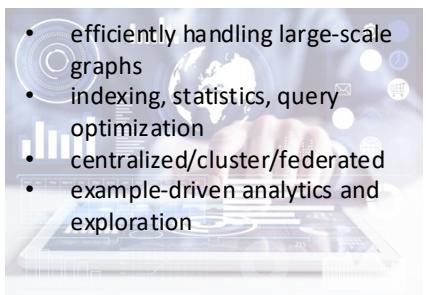
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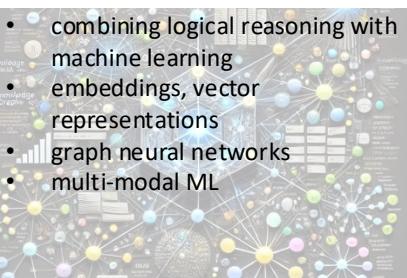
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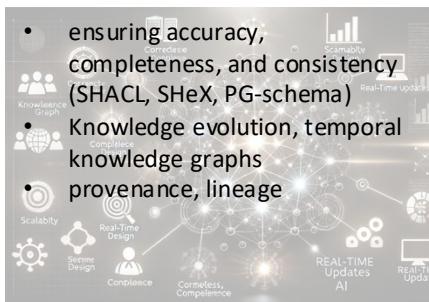


- Semantic Data Lakes
- information retrieval
- AutoML
- data catalogs
- explainable AI
- digital twins

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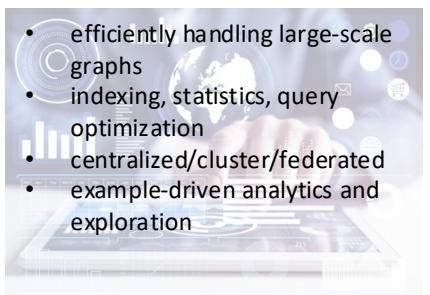
KGs as Enabling Technology



Knowledge graph challenges for GDBMS and AI

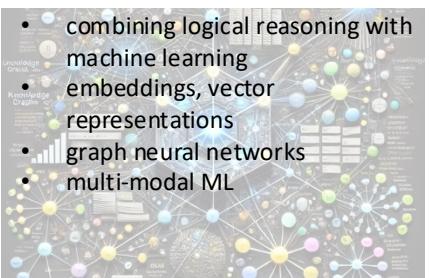
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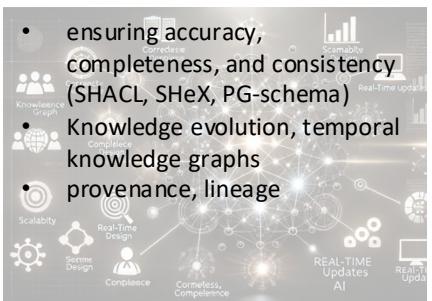
Generative AI



Data Modeling and Interoperability

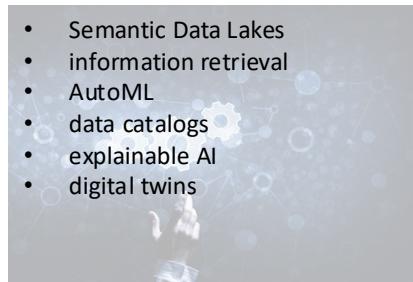
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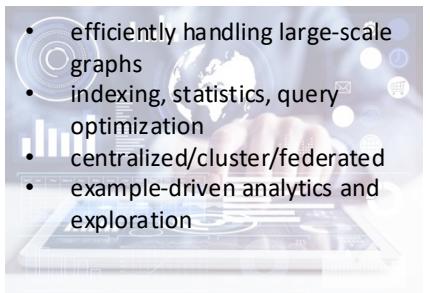
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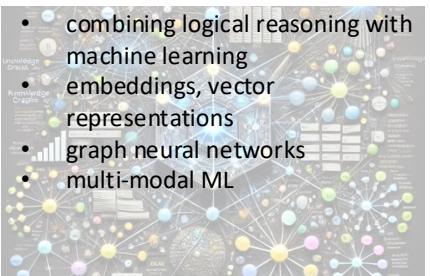
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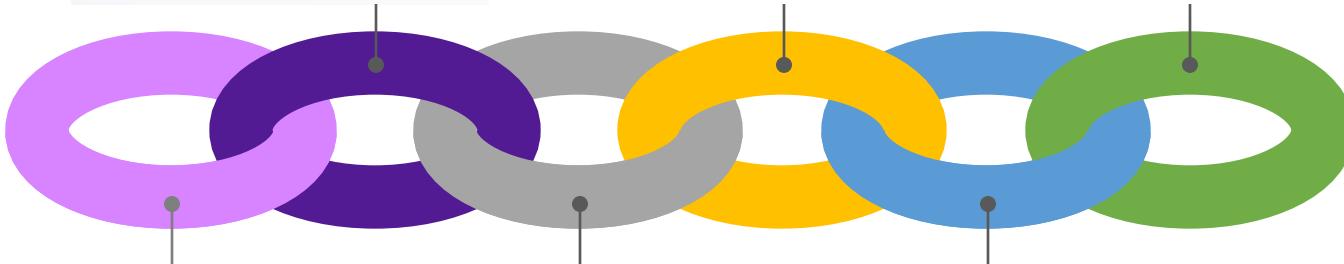
Generative AI

- LLMs and hallucinations
- Conversational agents
- Agentic AI
- GraphRAG

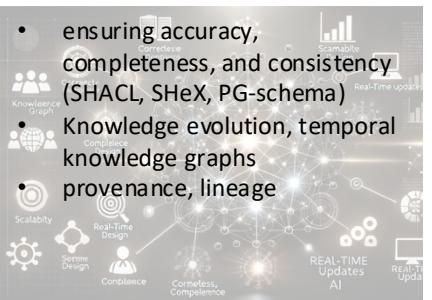


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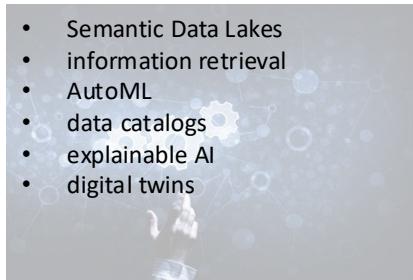


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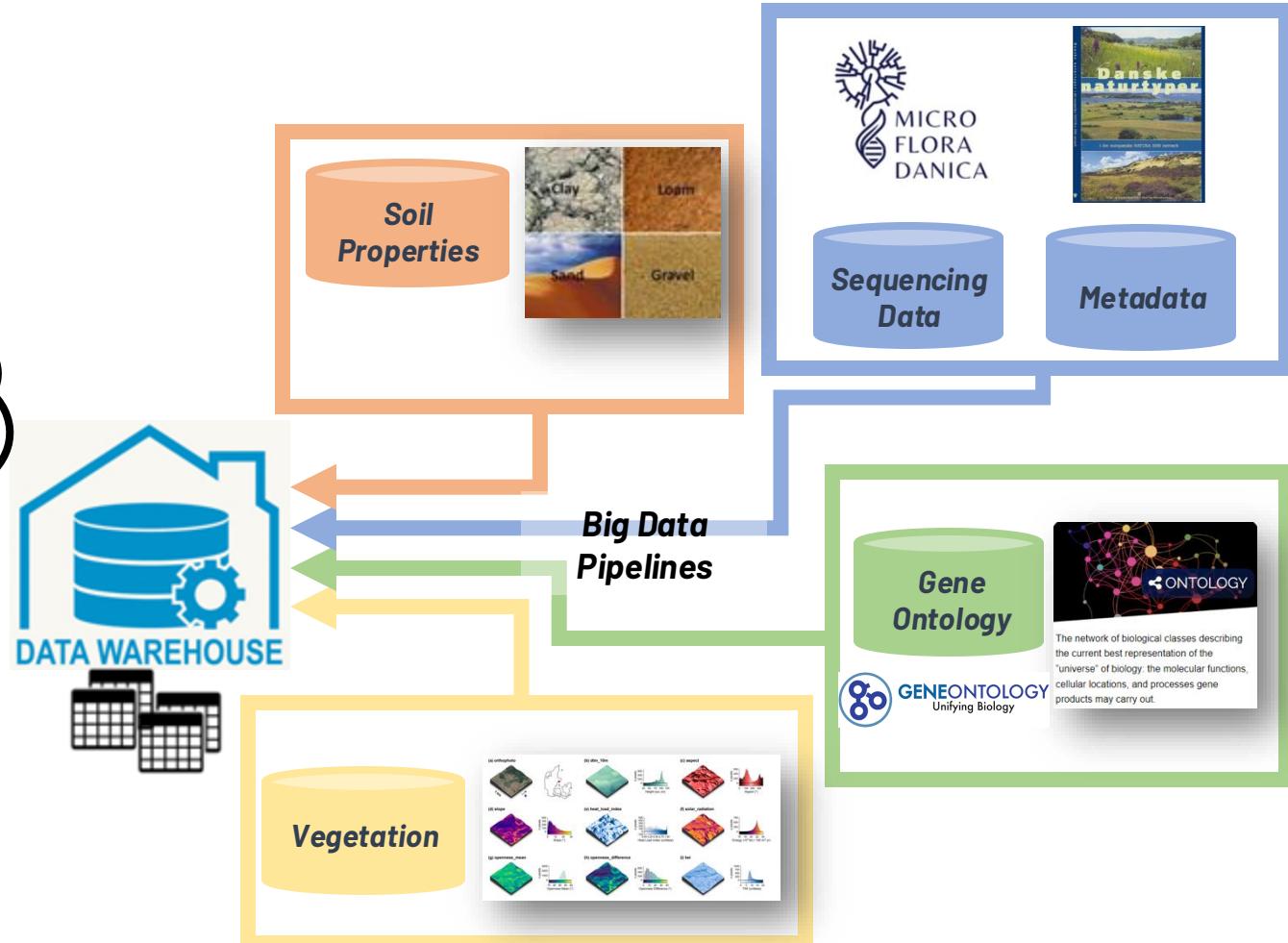
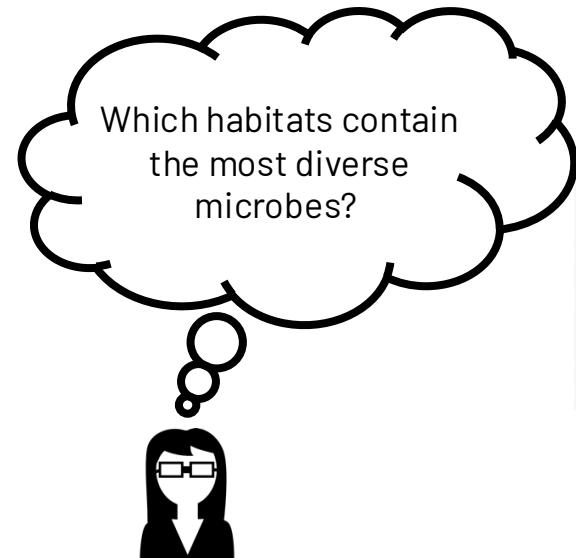


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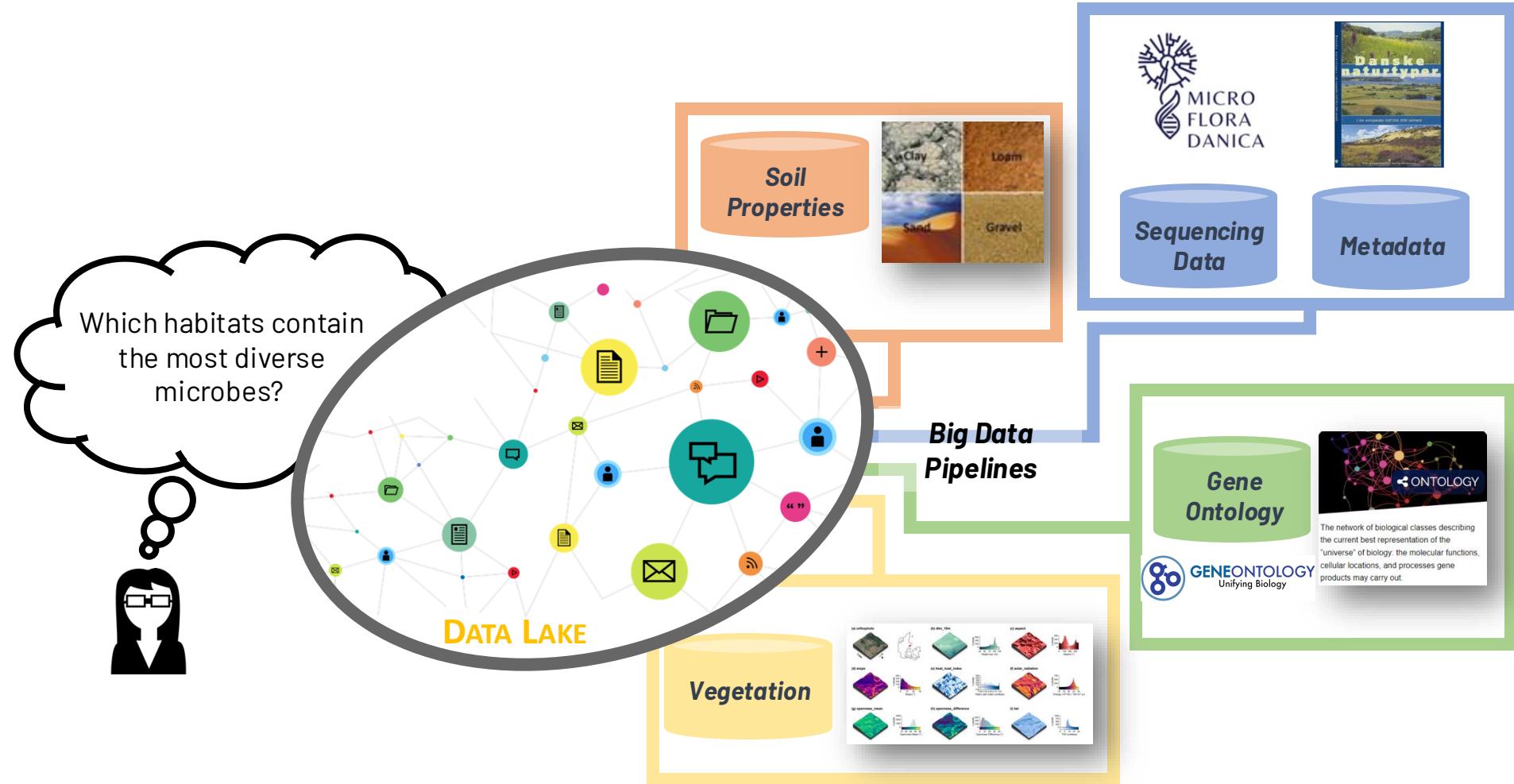
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Data Warehouses



Knowledge-Graph based Integration, Data Lakes, Data Fabrics, Enterprise Knowledge Graphs

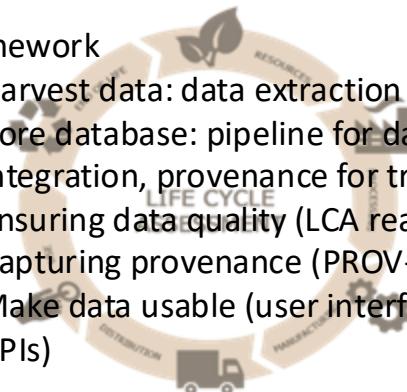


Use case
Lifecycle sustainability assessment

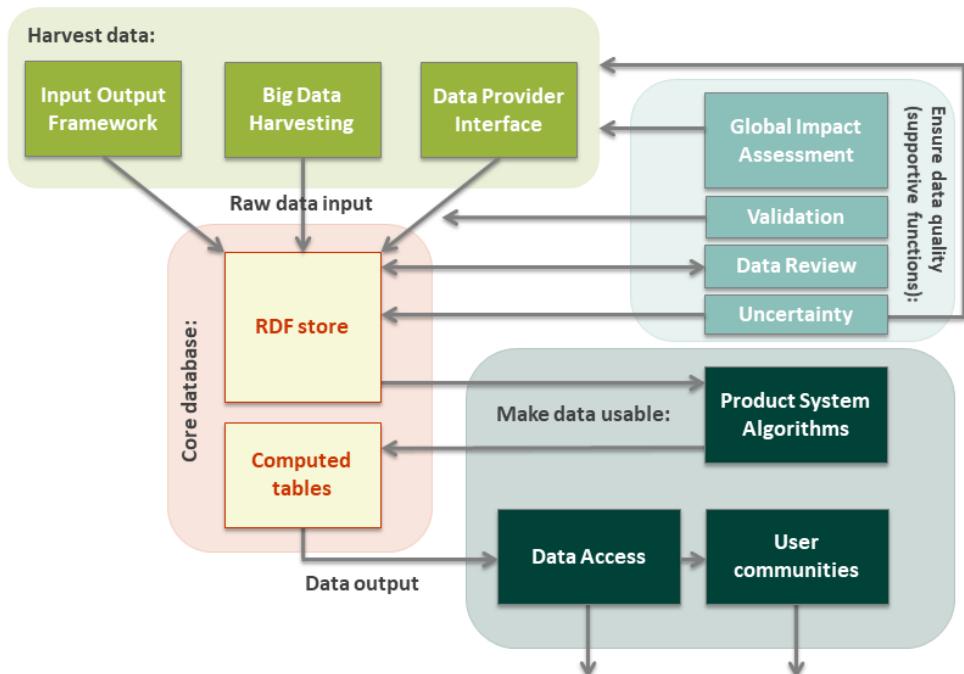
Goal
Overcoming closed data silos

Framework

- Harvest data: data extraction
- Core database: pipeline for data integration, provenance for tracing data
- Ensuring data quality (LCA reasoning)
- Capturing provenance (PROV-O)
- Make data usable (user interfaces and APIs)



140M triples of instance-level data
2K triples of schema-level data



Use case

Lifecycle sustainability assessment

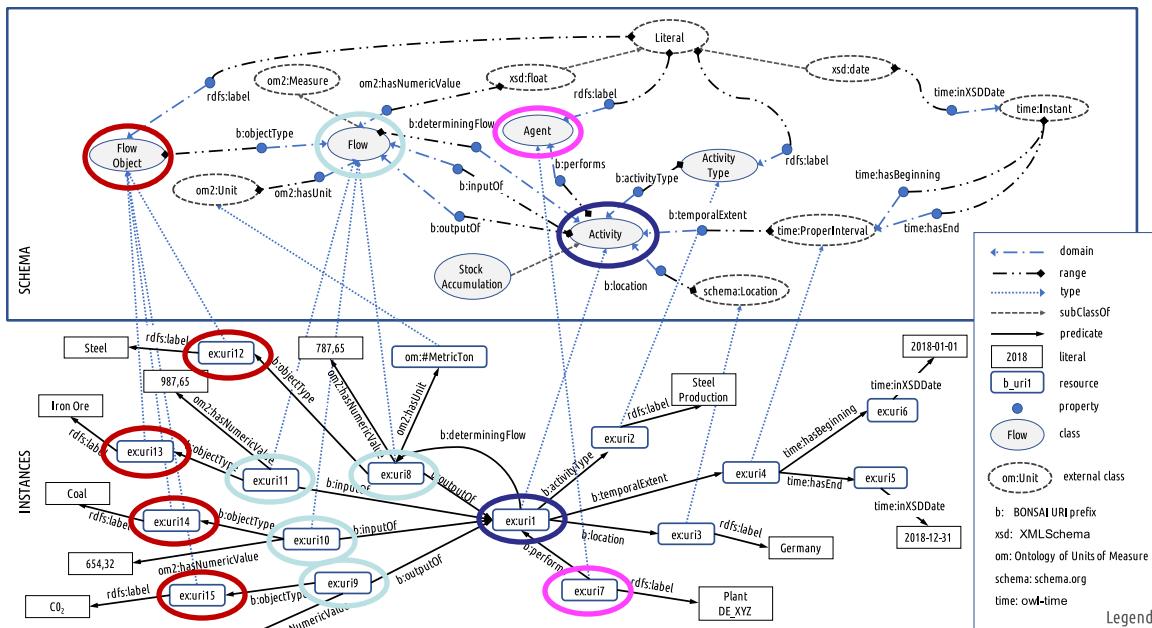
Goal

Overcoming closed data silos

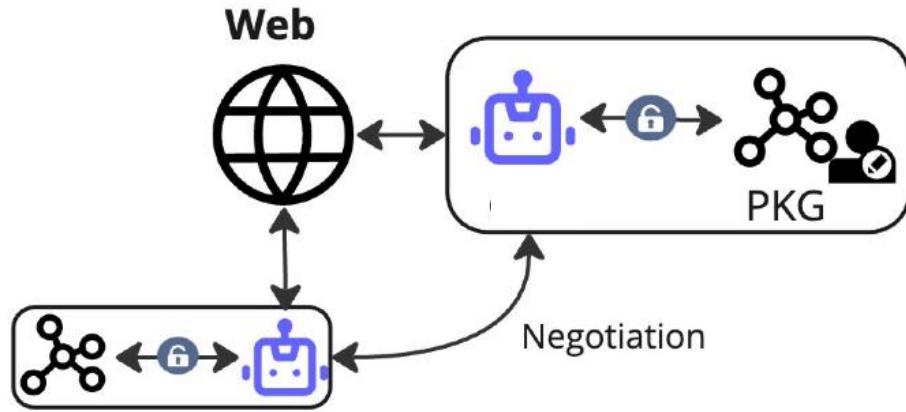
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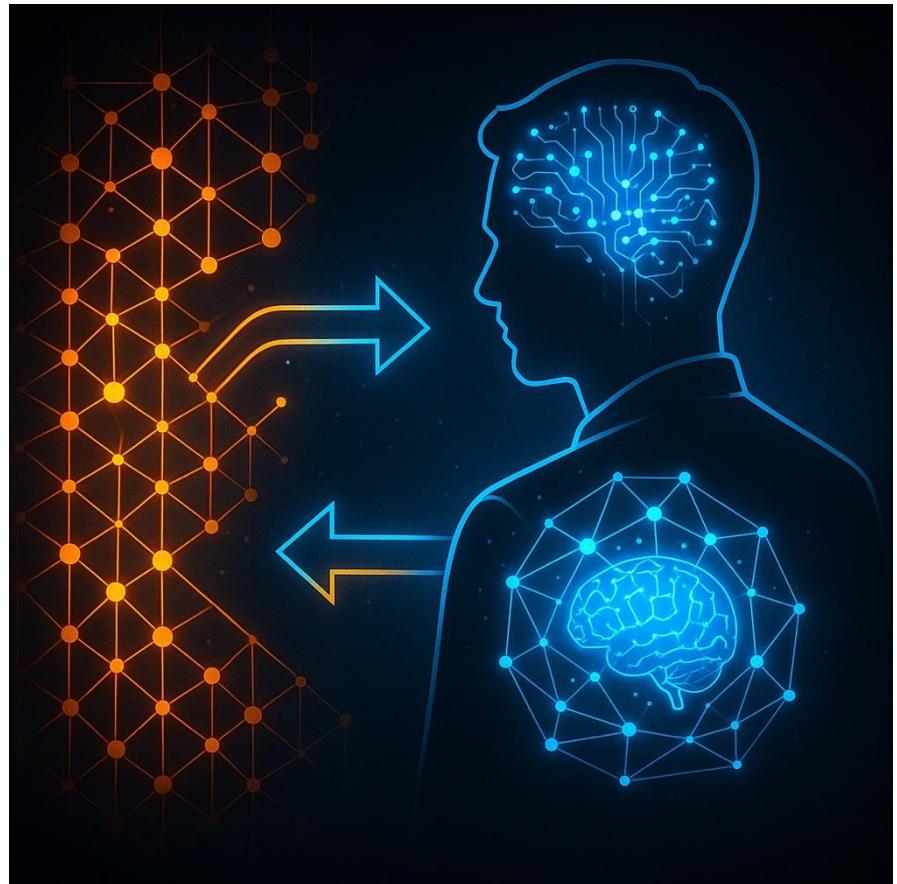


- Advancing Agentic AI
- Combine LLMs + Personal Knowledge Graphs (PKG)
- Goal
 - Personal automation with trust , structure, and control



Use case: planning a dinner date

- Agent assists in meal choice and shopping
- Coordinates between users' agents (diet, allergies, schedule)
- Learns from outcomes (e.g., heartburn → avoid next time)
- Challenge: autonomy + privacy + policy-aware reasoning

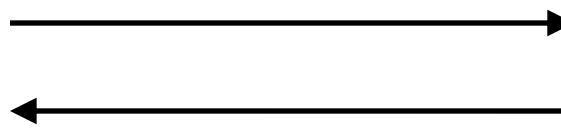


Use case: planning a dinner date

Sam: Jane is coming over
for dinner, propose Thai
food recipes.



recipes



No coriander, no shellfish (allergy)

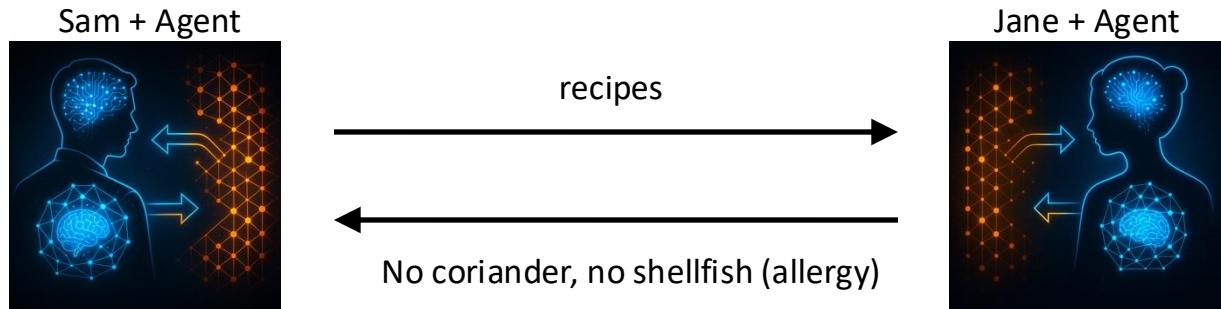


Use case: planning a dinner date

Sam: Jane is coming over for dinner, propose Thai food recipes.

→ agent proposes recipes (Sam is pre-diabetic)

→ find out which ones Jane probably likes



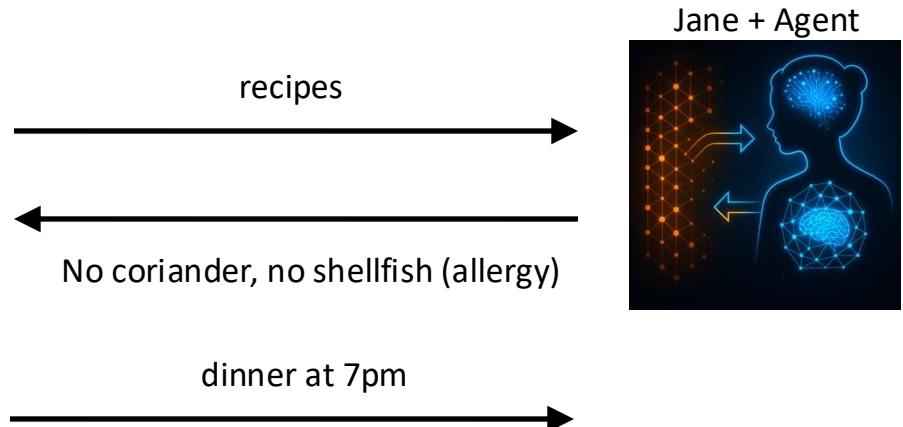
Use case: planning a dinner date

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Sam: picks one of the proposed options, asks agent to order ingredients
Sam: dinner at 7pm?



Use case: planning a dinner date

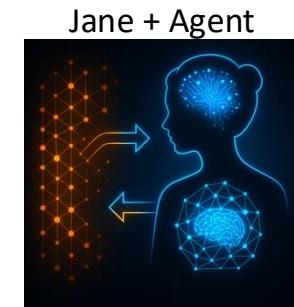
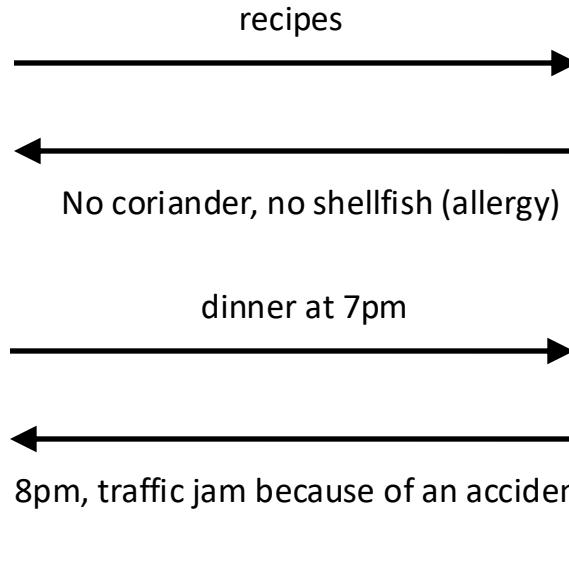
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Use case: planning a dinner date

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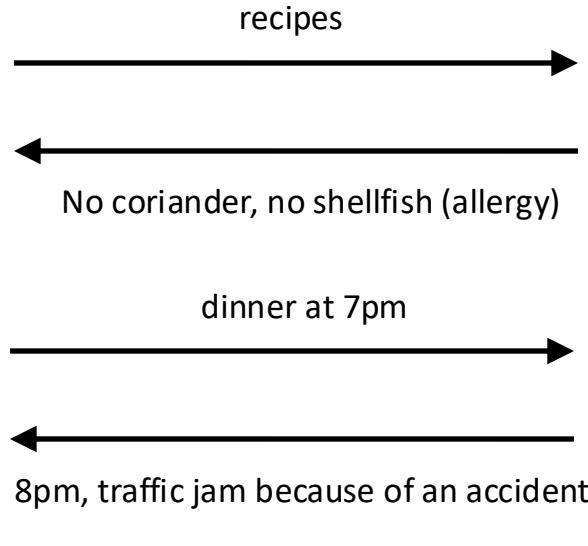
→ agent proposes recipes (Sam is pre-diabetic)

→ find out which ones Jane probably likes

Sam: picks one of the proposed options, asks agent to order ingredients

Sam: dinner at 7pm?

Sam: I have a heartburn
→ agent for the future



Some Topics Around SHACL

One of our research focus points

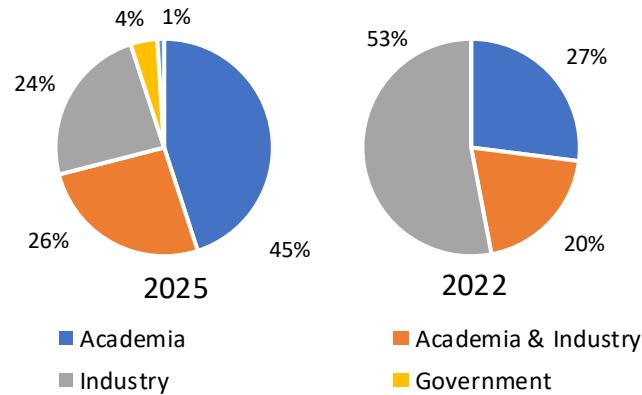
Bridging Gaps in RDF Validation

A community survey on the use of schema languages for RDF

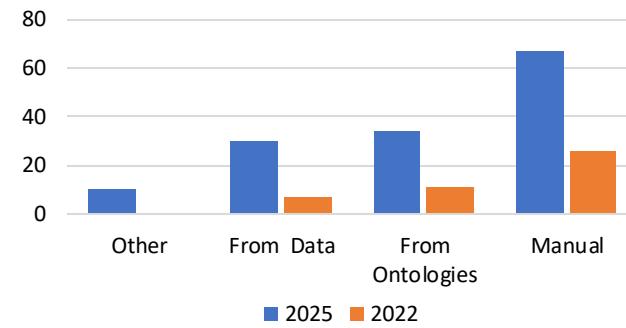
Language for validating RDF graphs against a set of [conditions](#)

W3C recommendation since July 2017: <https://www.w3.org/TR/shacl/>

SHACL allows validation of knowledge graphs in RDF by defining a [shapes graph](#) to validate a [data graph](#).

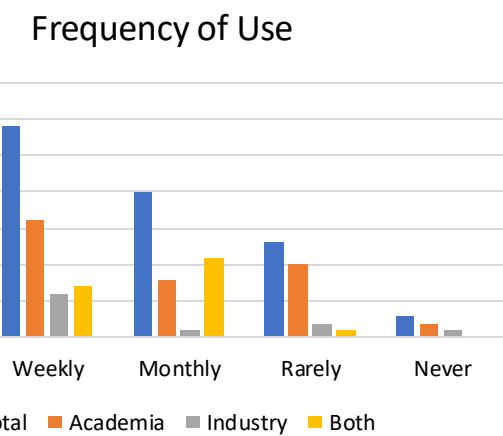
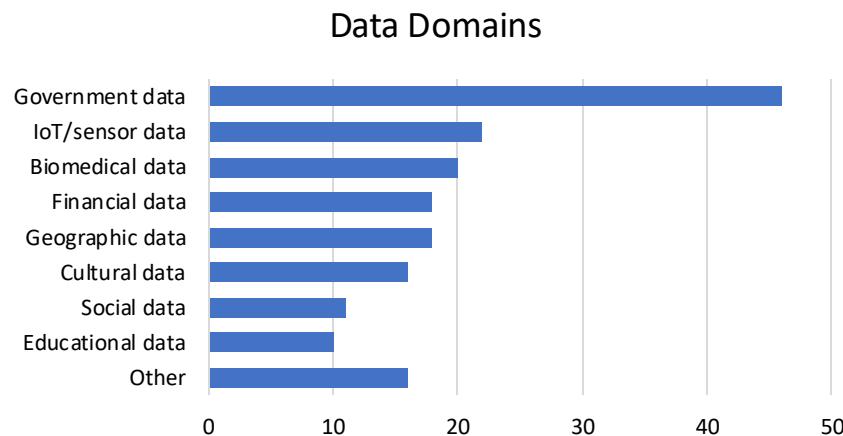
Respondent Background

- Online survey from 2025
- Comparison to a survey from 2022

Methods for Shape Creation

- Overwhelmingly manual
- Often created from other artifacts
- OWL Ontologies
- JSON Schema
- Conceptual Models

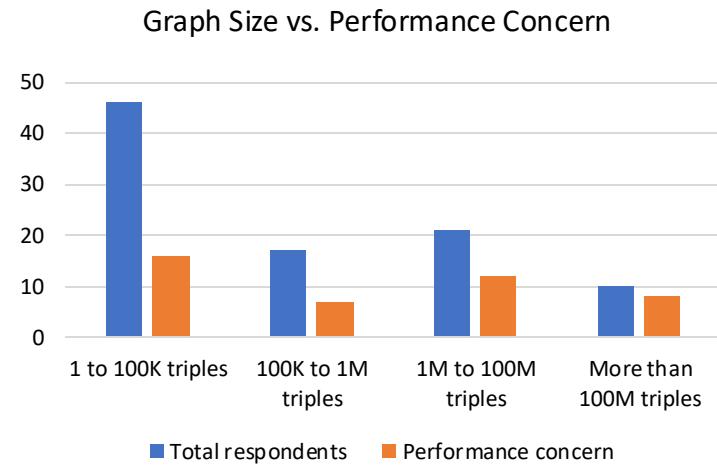
Data Domains and Frequency of Use



Issue / Limitation	Academia	Industry	Both
Documentation and tutorials	22	8	11
Community and tool support	20	11	8
Performance and scalability	17	9	11
Features or functionality	14	11	8
Missing constraint types	11	11	10

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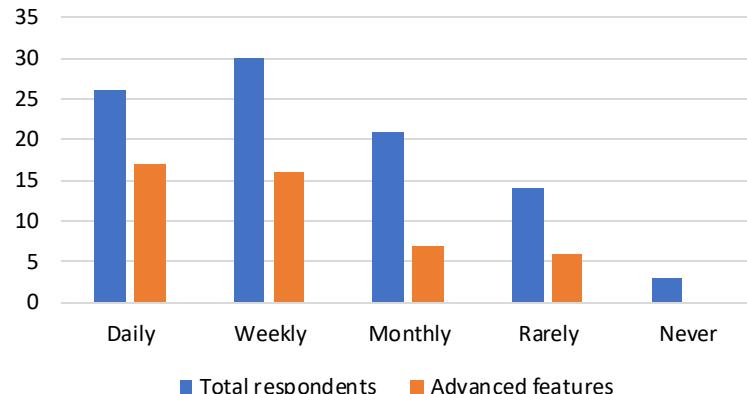
- Performance bottleneck for large datasets
- Few validators focus on performance
- Comparatively little academic literature
 - Idea: bring known techniques for query processing to SHACL/ShEx
 - Our work: [Compiling SHACL Into SQL](#) at ISWC 2024



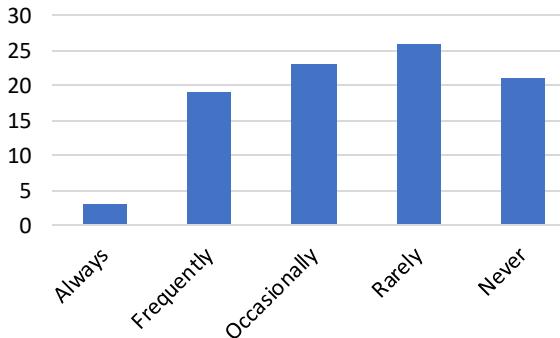
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- Advanced Features extends SHACL
 - Expressive power
 - Widen the scope of SHACL
- Need for greater expressiveness
- Need for expansion of SHACL's scope:
 - SHACL rules often cited

Frequency of Use vs. Advanced Features



SHACL-SPARQL Usage



Graph Subsetting and Neighborhoods

An alternative use for SHACL

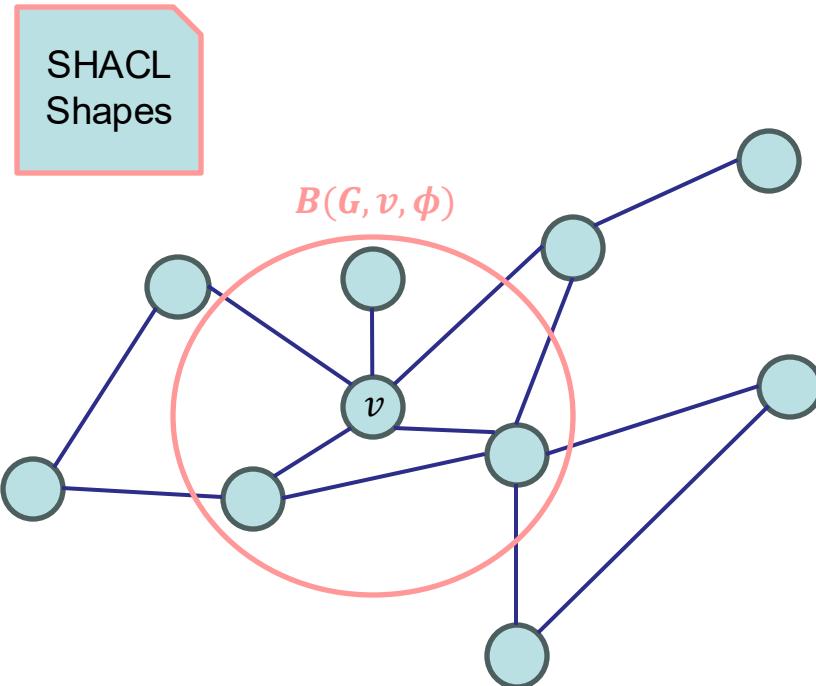
Goal:

Provide a **subgraph** that only contains triples that are “relevant”

We define the **neighborhood**: $B(G, v, \phi)$

- G a graph
- v a node
- ϕ a shape

What part of G is relevant to decide that v satisfies ϕ in G ?



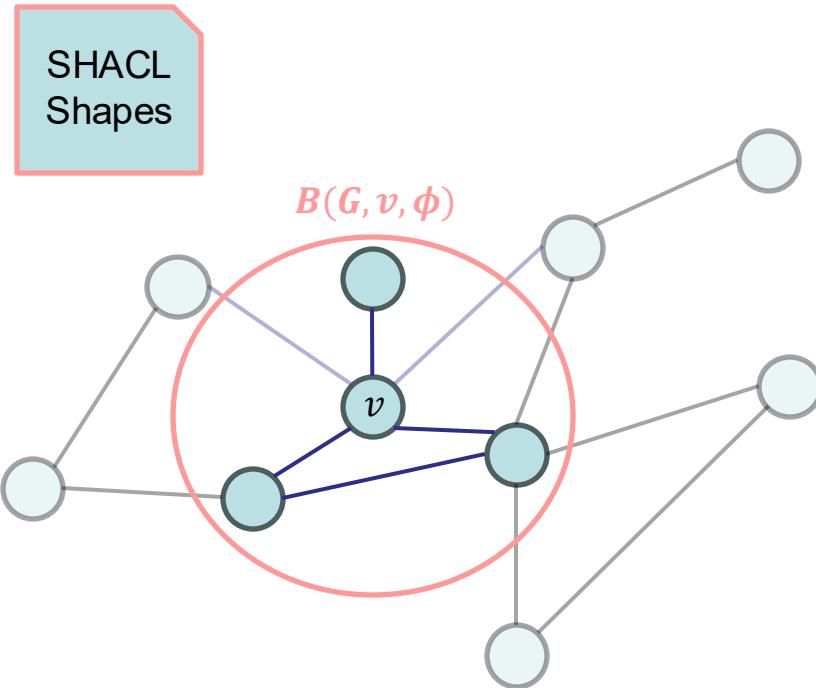
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**Sufficiency
Property**

If a node v satisfies a shape ϕ in a graph G , then:
 v also satisfies ϕ in G' for any subgraph G' with $B(G, v, \phi) \subseteq G' \subseteq G$.

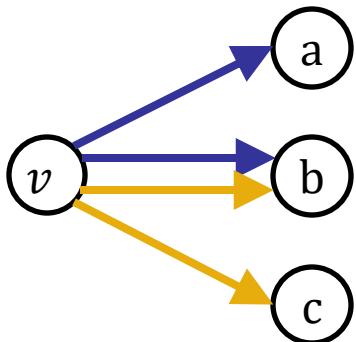
“Strong” sufficiency: it holds for all G' where $B(G, v, \phi) \subseteq G' \subseteq G$.

- Technical necessity
- Allows for leniency in implementations of neighborhoods

When defining neighborhoods we want to be both **deterministic** and **minimal**

Nonequality: $\neg eq(p, q)$

```
<myshape> sh:not [  
    sh:path <p>;  
    sh>equals <q>;  
].
```

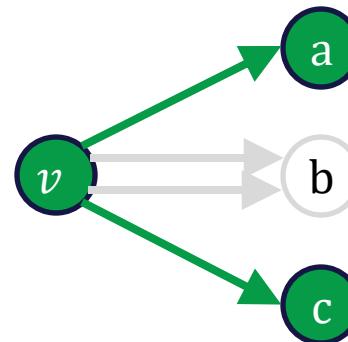
 G 

Options:

- Only edges to a and/or c
- All edges

 $B(G, v, \text{myshape})$

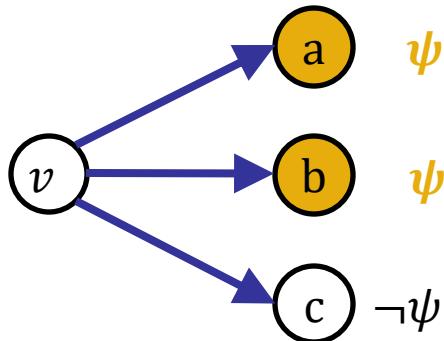
“symmetric difference”



Reasons:

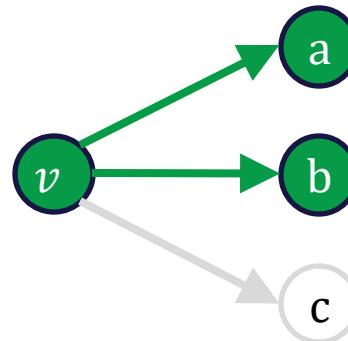
- Determinism
- Somehow minimal

```
<myshape> sh:property [  
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    sh:qualifiedValueShape  $\psi$  ;  
    sh:qualifiedMinCount 1 ;  
].
```

 G 

Options:

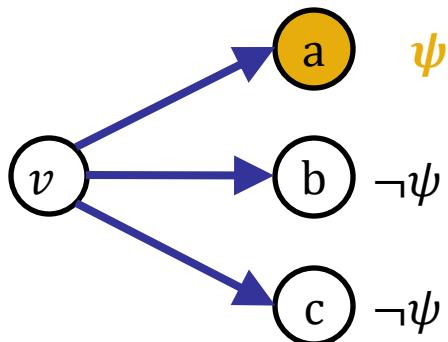
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 $B(G, v, \phi)$ 

Reasons:

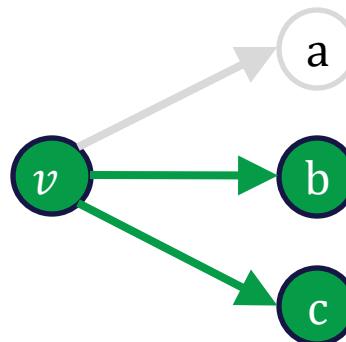
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- Somehow minimal

```
<myshape> sh:property [
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  sh:qualifiedValueShape ψ ;
  sh:qualifiedMaxCount 1 ;
].
```

 G 

Options:

- No edges
- Edge to a
- All edges

 $B(G, v, \phi)$ 

Reasons:

- Determinism
- Somehow minimal
- Adding edges to the neighborhood may not break sufficiency

We define $\mathbf{Frag}(G, S)$ as the union of all neighborhoods of nodes satisfying the shapes from S in G .

Let H be a shape schema, we define:

$$\mathbf{Frag}(G, H) := \text{Frag}(G, S)$$

where $S = \{\phi \wedge \tau \mid \tau \text{ is the target of } \phi \text{ in } H\}$

Conformance Property

If a graph G satisfies a schema H , then $\text{Frag}(G, H)$ also conforms to H .

Shape Fragments can be used for...

- Explaining validation
- Graph subsetting
- A notion of “coverage”

Common Foundations of SHACL, ShEx and PG-Schema

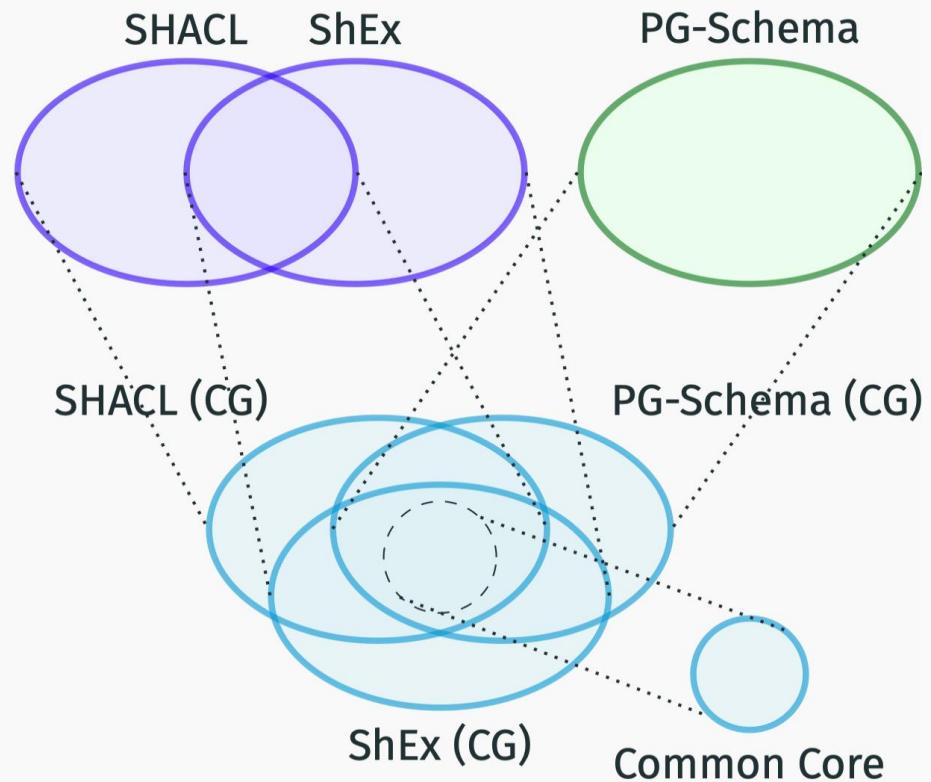
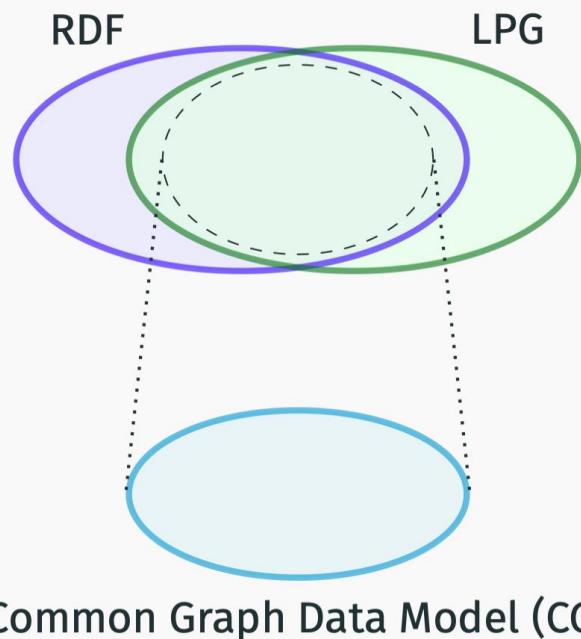
They are very different in nature, but closer than it seems

Understand differences and commonalities between SHACL, ShEx and PG-Schema

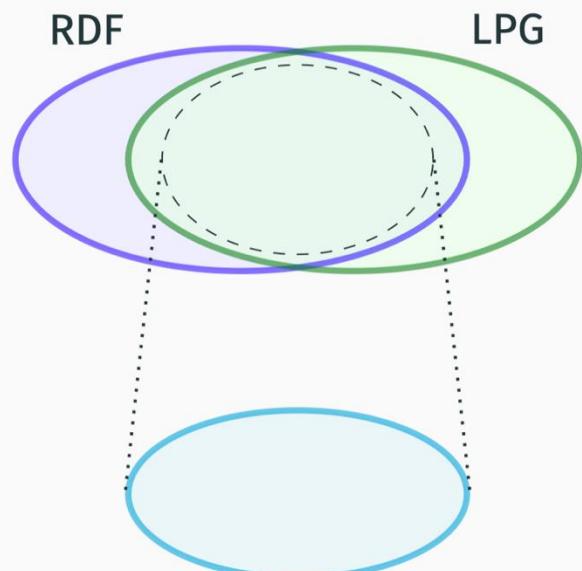
- **Users** are asking for this:
 - What are the fundamental differences? Is true interoperability possible?
- **Vendors** are asking for this:
 - What is actually used, and what is essential to support?
- **Designers** should be asking for this:
 - Why are there all these differences despite the similar objectives?
 - Do the superficial differences matter?

	SHACL	ShEx	PG-Schema
Data Model	RDF	RDF	LPG
Paradigm	Logical constraints	Regular expressions	Type-based + rich key constraints

- Their respective theoretical foundations seem only loosely related
- Defined for different data models
- Defined by different communities



Distilling the Common Graph Data Model



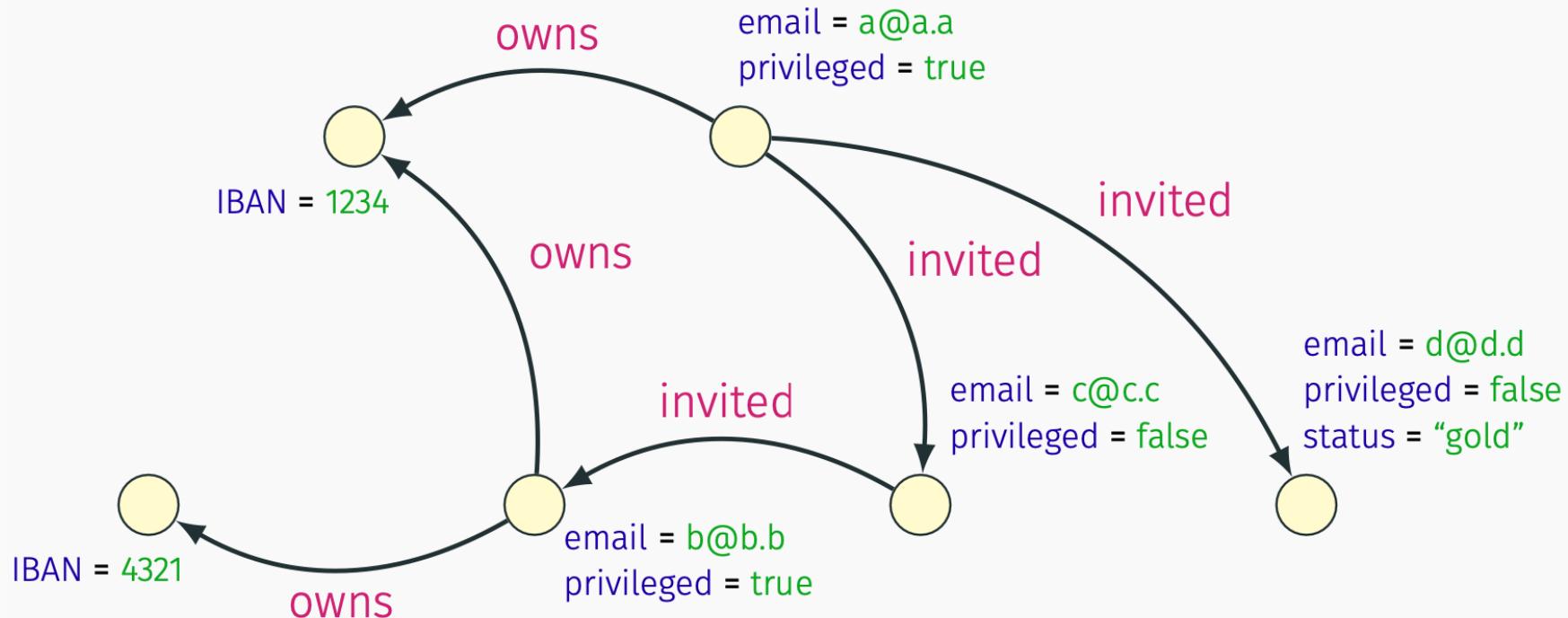
Features not present in both RDF and LPG are removed.

RDF Gives up:

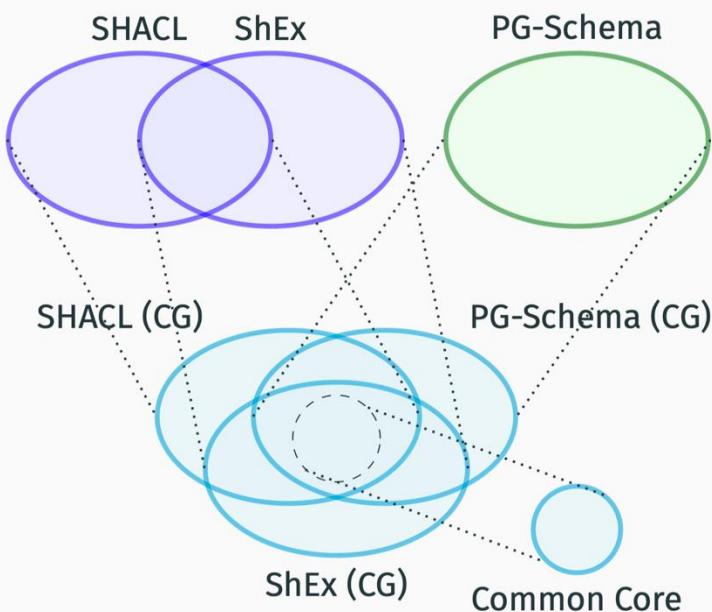
- **Nodes** cannot be compared with an IRI
- **Predicates** ...
 - associate at most one value with a node
 - cannot be compared with a node

LPG Gives up:

- **Nodes** do not have labels
- **Edges** ...
 - have exactly one label
 - have no properties
 - are identified by label and endpoints



Distilling the three schema languages



A **common shape** describes the graph's structure around a **focus node** or value.



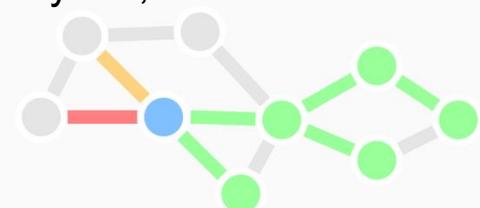
A **selector** is a simple shape that indicates **focus nodes** or values.



A **schema** is a set of selector-shape pairs.



A graph G **conforms to** a schema S if, for each selector-shape pair (sel, s) in S , for every focus v indicated by sel , v has shape s



SHACL and ShEx give up

- disjunctions and negations,
- nesting of shapes.

```
<s> sh:or (
  [ sh:path <invited>; sh:minCount 1 ]
  [ sh:not [ sh:path <status> sh:hasValue "gold" ] ).
```

SHACL and PG-Schema give up

- unbounded path expressions.
- counting over multi-edge paths.

```
<s> sh:path [ sh:zeroOrMorePath <invited> ];
  sh:minCount 100 .
```

PG-Schema gives up

- closing properties and edges independently,
- testing properties under star.

ShEx gives up recursion.

DEFINITION 12 (COMMON SHAPE). A common shape φ is an expression given by the grammar

$$\varphi ::= \exists \pi \mid \exists^{\leq n} \pi_1 \mid \exists^{\geq n} \pi_1 \mid \exists \mathbb{C} \wedge \nexists \neg P \mid \varphi \wedge \varphi .$$

$$\mathbb{C} ::= \{\} \mid \{k : \mathbb{V}\} \mid \mathbb{C} \& \mathbb{C} \mid \mathbb{C} \mid \mathbb{C} .$$

$$\pi_0 ::= [k = c] \mid \neg[k = c] \mid \mathbb{C} \& \top \mid \neg(\mathbb{C} \& \top) \mid \pi_0 \cdot \pi_0 .$$

$$\pi_1 ::= \pi_0 \cdot p \cdot \pi_0 \mid \pi_0 \cdot p^- \cdot \pi_0 \mid \pi_0 \cdot k \mid k^- \cdot \pi_0 .$$

$$\bar{\pi} ::= \pi_0 \mid p \mid \bar{\pi}^- \mid \bar{\pi} \cdot \bar{\pi} \mid \bar{\pi} \cup \bar{\pi} .$$

$$\pi ::= \bar{\pi} \mid \bar{\pi} \cdot k \mid k^- \cdot \bar{\pi} \mid k^- \cdot \bar{\pi} \cdot k' .$$

where $n \in \mathbb{N}$, $P \subseteq_{fin} \mathcal{P}$, $k, k' \in \mathcal{K}$, $c \in \mathcal{V}$, and $p \in \mathcal{P}$.

- A common **framework** to talk about SHACL, ShEx, and PG-Schema, compare their core mechanisms and expressive power:
 - a high-level notion of a shape-based graph schema;
 - a uniform syntax for shapes and selectors.
- A **foundation** for automating interoperability:
 - a data model that can be supported by both RDF and LPG;
 - a schema language that can be compiled to SHACL, ShEx, and PG-Schema.

Master Thesis Topics

- Schema-related topics:
 - Creating a fast and scalable SHACL validator
 - Generating RDF data from SHACL shapes
 - Validating virtual graph data
 - Mining schemas from graph data
- Applied Data Management
 - Integrating biological datasets into graph data
 - Federated exploration of microbial and environmental data
- Evolving graph data
 - Visualizing evolving graph data
 - Benchmarking evolving property graphs
- Please contact us for more details, or to sit together and develop a topic!

Course Feedback

Please provide feedback to the course using the form on TUWEL (anonymous)



Exam Information

- Project hand-in: 18th of January 2026
- Written exam: 9th of January 2026
- Second chance: 2nd of March 2026
- Points: Project (60) + Exam (40)
 - You must pass both (at least 50%)
 - For the exam, the last attempt counts
- Exam structure
 - Theory: a set of yes/no questions
 - Understanding and interpreting queries/schemas
 - Either open questions;
 - Or complex multiple-choice questions