188.399 Einführung in Semantic Systems

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Contents

1 Introduction

This summary is for the course "Introduction to Semantic Systems" (course code: 188.399) at the Vienna University of Technology (TU Wien) and was created for the Winter Semester 2024 in preparation for the exam. The document covers most of the essential topics discussed in the course, focusing on key concepts and practical applications in semantic systems. While it aims to provide a comprehensive review of the material, some advanced topics might not be explored in full depth.

This summary is available on GitHub. If you find typos, errors, want to add content (such as additional explanations, links, figures, or examples), or wish to contribute, you can do so at the following repository:
`https://github.com/mtiessler/188.399-Introduction-To-Semantic-Systems-Summary-TUW/blob/main/ISS_Summary.pdf`.

If the URL does not work, you can locate it on GitHub using the following details:

- **User**: mtiessler
- **Repo-Name**: 188.399-Introduction-To-Semantic-Systems-Summary-TUW

2 What is an Ontology

Ontology is derived from the Greek words *ontos* (being) and *logos* (word), meaning the study or systematic explanation of existence.

In philosophy, ontology is a branch concerned with categorizing and explaining existence. Aristotle (400 BC) made early attempts to establish universal categories for classifying everything that exists.

2.1 Definition

According to the **Merriam-Webster dictionary**:

- A branch of metaphysics concerned with the nature and relations of being.
- A particular theory about the nature of being and kinds of existents.

In the context of knowledge representation, **Studer (1998)** defines ontology as seen in figure 1. This definition highlights several key aspects:

- **Formal**: Ontologies are machine-readable and interpretable.
- **Explicit**: Concepts, properties, functions, and axioms are clearly defined.
- **Shared**: Ontologies are agreed upon and shared by a community.
- **Conceptualization**: They provide an abstract model of some phenomena in the world.

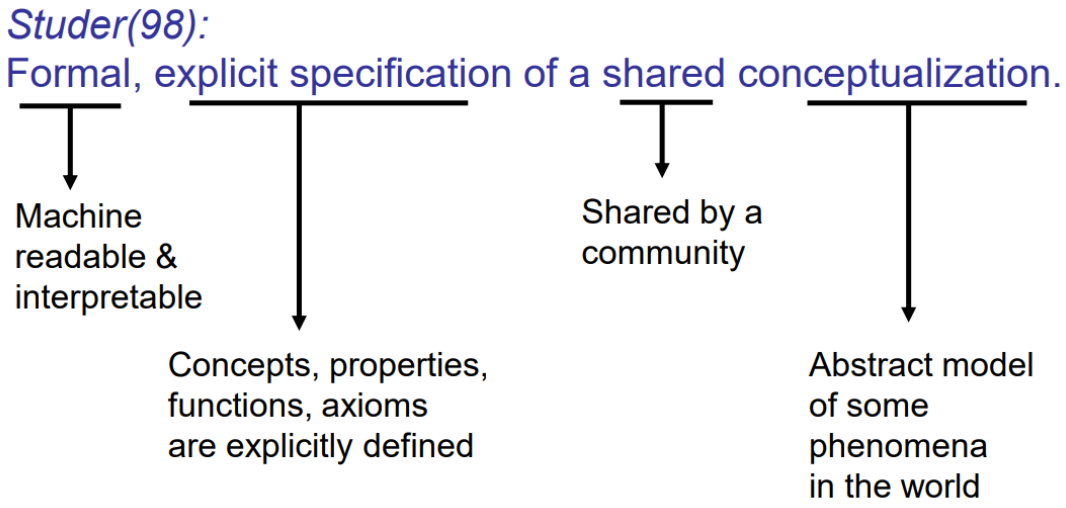

Figure 1: Ontology definition

2.2 Types and Categories

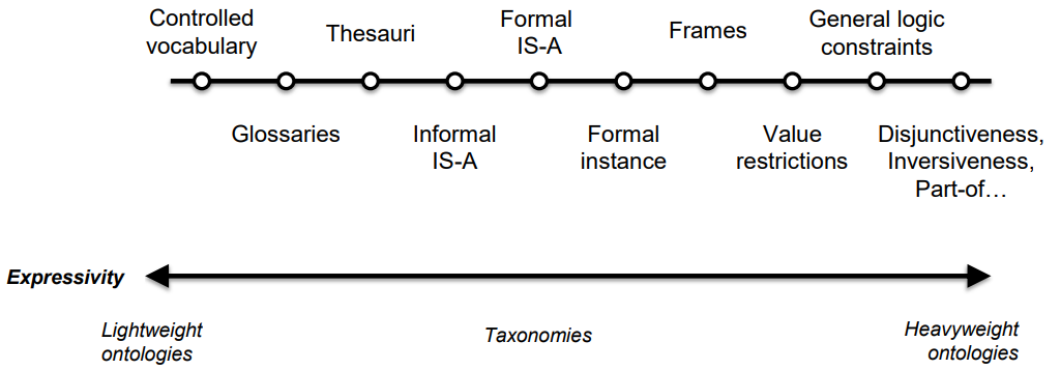

Figure 2: Ontology Types

2.2.1 Lightweight

Lightweight ontologies are simplified frameworks for organizing and defining knowledge. Key types include:

- **Controlled Vocabulary**: A finite list of terms, often used in catalogs.
  - **Example**: A library catalog listing book titles, authors, and genres (e.g., "Fiction," "Science," "Biography").
- **Glossary**: A controlled vocabulary with informal definitions provided in natural language.
  - **Example**: A glossary of medical terms, such as:
    - "Hypertension: High blood pressure."
    - "Cardiology: The branch of medicine dealing with the heart."
- **Thesauri**: A controlled vocabulary where concepts are connected through various relations:
  - **Equivalency**: Synonym relations between concepts.
    - **Example**: "Automobile" and "Car."
  - **Hierarchies**: Subclass and superclass relationships.
    - **Example**: "Dog" is a subclass of "Animal."
  - **Homographs**: Handling of homonyms (terms with identical spellings but different meanings).
    - **Example**: "Bank" (a financial institution) vs. "Bank" (the side of a river).
  - **Associations**: Relations between similar or related concepts.
    - **Example**: "Wine" is related to "Grape."

A popular example of a lightweight ontology is the "Friend of a Friend" (FOAF) ontology, which defines relationships between people in social networks.

2.2.2 Taxonomies

Taxonomies provide a hierarchical system of grouping concepts or entities. The term originates from the Greek words *taxis* (order, arrangement) and *nomos* (law, science). Types of taxonomies include:

- **Informal IS-A Hierarchy**: An explicit hierarchy of classes where subclass relations are not strict. For example, the index of a library.
- **Formal IS-A Hierarchy**: An explicit hierarchy of classes with strict subclass relations.
- **Formal Instance**: A hierarchy that includes explicit class structures, strict subclass relations, and allows *instance-of* relations.

A taxonomy can be defined as a controlled vocabulary organized into a hierarchical structure. As seen in 3.

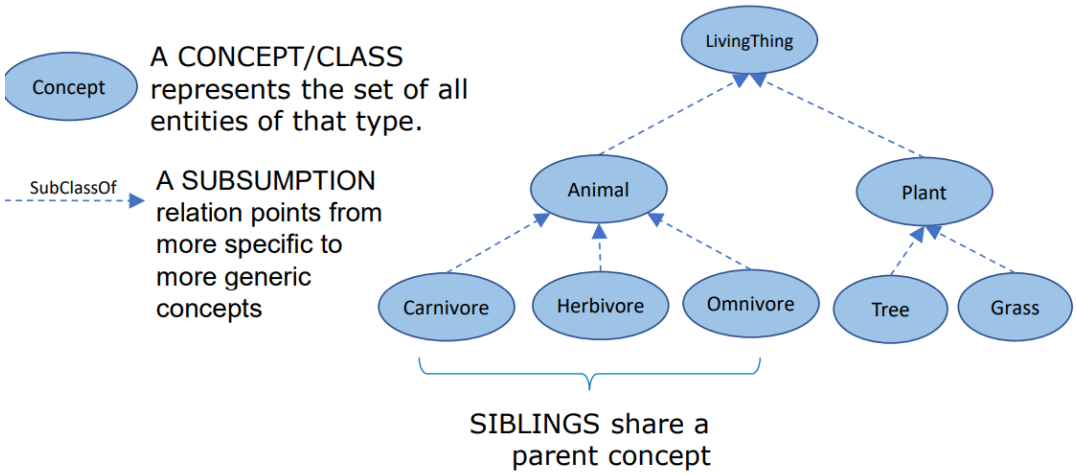

Figure 3: Taxonomy Example

Key concepts in formal taxonomies include:

- **SubClassOf**: A relation pointing from a more specific concept to a more generic concept.
- **Concept/Class**: Represents the set of all entities of a specific type.
- **Subsumption**: A specialization relation pointing from a specific concept to a generic one.

Subsumption/SubClass/Specialization Relation (in Formal IS-A Taxonomies) Semantics (Meaning): Subsumption in formal IS-A taxonomies ensures that if one class is a subclass of another, all instances of the subclass are also instances of the superclass. For example, if *Herbivore* is a subclass of *Animal*, all instances of *Herbivore* are also instances of *Animal*.

Common Mistake: Subsumption is often mistakenly used to represent other types of relations, such as *part-of* (meronymy), which denotes a part-to-whole relationship rather than a class hierarchy.

2.2.3 Heavyweight

Heavyweight ontologies provide a rigorous framework for defining and organizing knowledge with a strong emphasis on logic and formal specifications. Key characteristics include:

- **Rigorous Definition and Organization of Concepts**: Concepts and their relationships are precisely defined, ensuring clarity and reducing ambiguity.
- **Focus on Logic**: Heavyweight ontologies prioritize formally correct deductions and inferences, enabling reliable reasoning and decision-making.
- **Careful Formal Specification**: A formal specification ensures consistency and eliminates contradictions within the ontology.

Heavyweight ontologies are often used in applications requiring advanced reasoning, such as artificial intelligence, semantic web technologies, and complex domain modeling. They aim to create a shared, consistent understanding of knowledge that can be processed by both humans and machines.

Examples of Heavyweight Ontologies

- **Frames**: Frames provide structured representations for defining classes and their properties.
  - **Example**: In a medical ontology, the frame for "Disease" might include properties such as "Symptoms," "Causes," and "Treatment."
- **Value Restrictions**: These enforce constraints on the values that properties can take.
  - **Example**: In a wine ontology, "Wine color" might be restricted to values like "Red," "White," or "Rosé."
- **General Logic Constraints**: These involve the application of logical rules to ensure consistency across the ontology.
  - **Example**: If "Animal" is defined as disjoint from "Plant," no instance can belong to both classes simultaneously.
- **Disjunctiveness**: Ensures that certain concepts are mutually exclusive.
  - **Example**: "Male" and "Female" in a gender ontology might be disjoint concepts.
- **Inversiveness**: Defines inverse relationships between properties.
  - **Example**: If "Parent" is a property, its inverse would be "Child."
- **Part-of Relationships**: These express compositional relationships.
  - **Example**: "Engine" is a part of "Car."

2.3 Ontology

Ontology is a **taxonomy** extended with additional relations and further constraints, providing a more comprehensive framework for modeling knowledge. Relations within an ontology are directed, pointing from a **Domain** concept to a **Range** concept. These relations can also include:

- **Inverse Relations**: Relations that allow bidirectional reasoning. For example, if "Tom eats Jerry," the inverse relation could be "Jerry is eaten by Tom."
- **Disjoint Concepts**: Concepts that describe non-overlapping instance sets, ensuring that instances belong to distinct categories. For example, *Carnivore* and *Herbivore* may be disjoint concepts.

2.3.1 Mechanics

The mechanics of an ontology focus on the logical and structural rules governing the relationships and organization of concepts, as seen in figure 4:

- Establishing the **Domain** and **Range** of relations to clarify which concepts are linked.
- Defining and maintaining **consistency** among concepts, relations, and instances.
- Implementing **constraints**, such as disjointness or cardinality, to refine the ontology's structure and enforce rules.

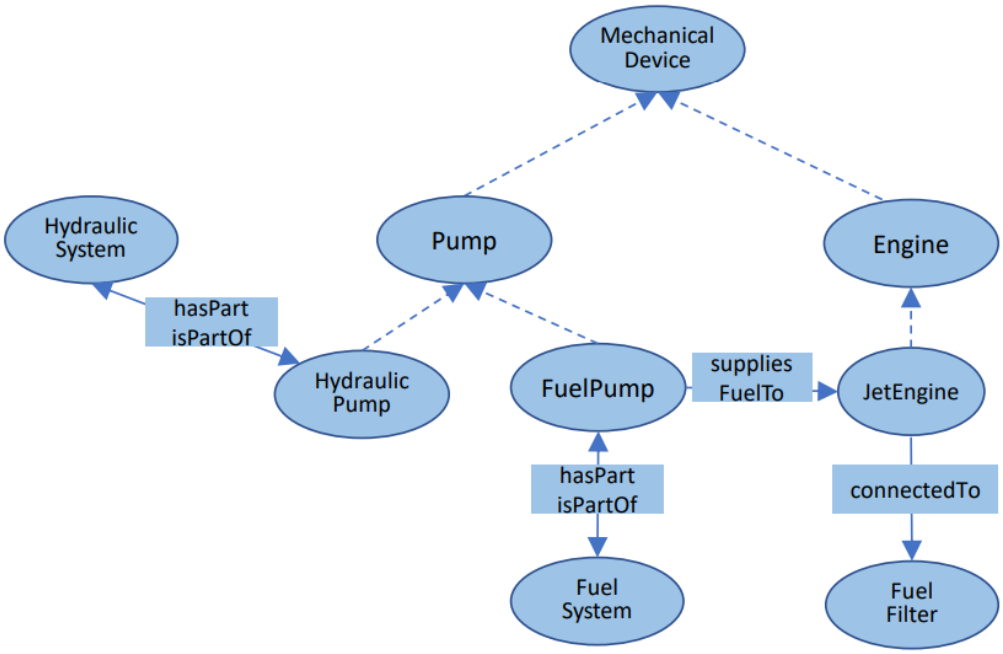

Figure 4: Ontology Mechanics

2.3.2 Instances/Entities

Instances or entities represent individual objects in the universe of discourse. They provide specific examples or metadata tied to the defined concepts in an ontology. This can be seen in 5.

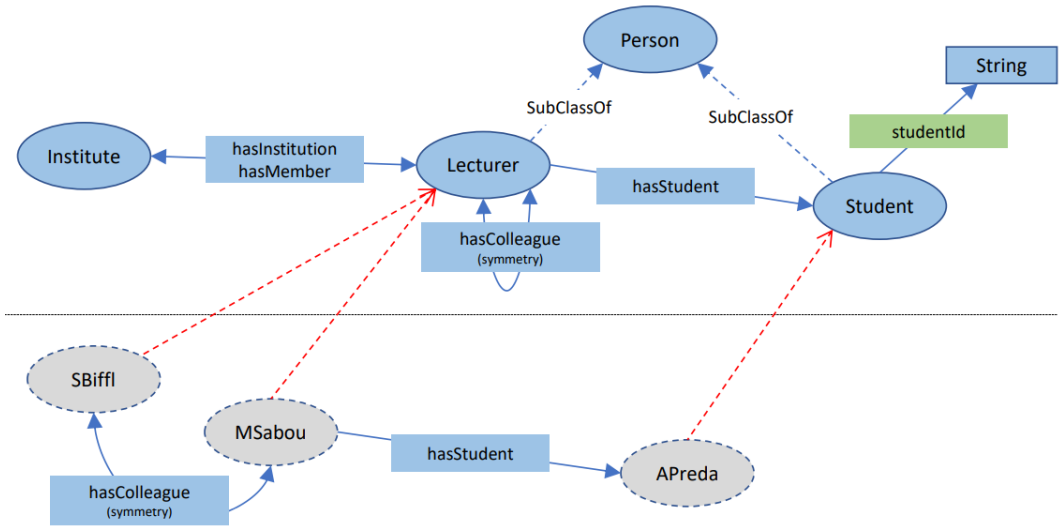

Figure 5: Ontology instances

Key aspects include:

- **Instance Representation**: An instance corresponds to a real-world entity and is associated with one or more concepts. For example:
  - *Tom is a Carnivore.*
  - *Jerry is an Animal.*
  - *Tom eats Jerry.*
- **Typing**: An instance is typed with respect to a concept, meaning that it is classified as being of a particular type. For example, "Tom" is an instance of the concept *Carnivore*.
- **Relations Between Instances**: Instances are connected through defined relations within the ontology, such as "eats" in the example above.

2.4 Description Logics

Description Logics (DL) are a family of formal knowledge representation languages used as the foundation for creating machine-readable ontologies. They are particularly suited for the Semantic Web and are based on a subset of First-Order Logics. DL provides a framework for representing and reasoning about knowledge in a structured and formal way.

2.4.1 Introduction

Description Logics aim to:

- Represent knowledge in a way that is both human-readable and machine-readable.
- Enable computers to reason with data and draw logical conclusions.
- Provide a formal basis for defining and organizing ontologies.

A formal, logic-based language in DL offers:

- **Syntax**: Defines which expressions are considered valid.
- **Semantics**: Provides the meaning of those expressions.
- **Calculus**: Defines how to compute and determine the meaning of expressions.

Semantic Web languages, such as OWL (Web Ontology Language), are built on Description Logics.

2.4.2 General DL Architecture

The general architecture of a Description Logic system (can be seen in 6), involves the following components:

- **Knowledge Base (KB)**: Composed of:
  - **TBox** (Terminological Knowledge): Contains definitions of concepts, attributes, and properties of a domain. For example:

    $$Writer \equiv Person \sqcap \exists author.Book$$

  - **ABox** (Assertional Knowledge): Contains information about specific individuals or entities. For example:

    $$Writer(GeorgeOrwell)$$

- **Inference Engine**: A component that reasons with the knowledge base to infer new information or check consistency.
- **Interface**: The mechanism for users or systems to interact with the ontology.

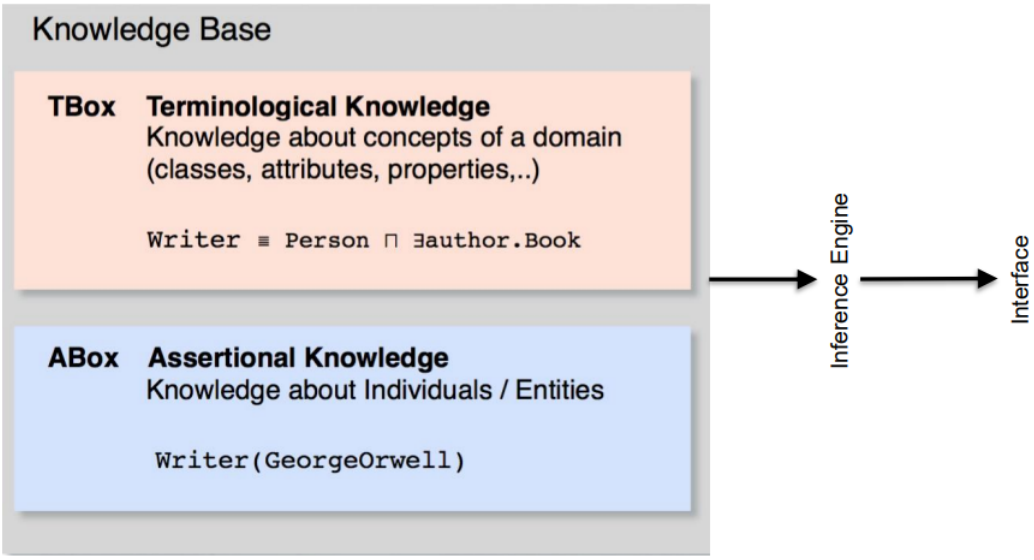

Figure 6: DL architecture

2.4.3 Notation / Syntax

The syntax of DL includes:

- **Atomic Types**:
  - Concept Names: $A, B, ...$
  - Special Concepts:
    - $\top$: Universal concept (all objects in the domain).
    - $\bot$: Bottom concept (empty set).
  - Role Names: $R, S, ...$
- **Constructors**:
  - Negation: $\neg C$
  - Conjunction: $C \sqcap D$
  - Disjunction: $C \sqcup D$
  - Existential Quantifier: $\exists R.C$
  - Universal Quantifier: $\forall R.C$

Examples:

- $Writer \equiv Person \sqcap \exists author.Book$
- $Novel \equiv Prose$
- $Novel \sqsubseteq Book$
- $Herbivore \sqsubseteq \neg\ Carnivore$
- $PetOwner \sqsubseteq Person \sqcap \exists hasPet.Animal$
- $Carnivore \sqsubseteq Animal \sqcap \forall eats.Animal$

2.4.4 Semantics

Description Logics rely on model-theoretic semantics, where an interpretation consists of:

- A **domain of discourse** (Δ): A collection of objects.
- **Interpretative Functions** (I): Functions mapping:
  - Classes (concepts) to sets of objects in the domain.
  - Properties (roles) to sets of pairs of objects.

In a DL, a class description characterizes the individuals that are members of that class, allowing precise reasoning and inference based on defined relationships and constraints.

It can be better seen in 7:

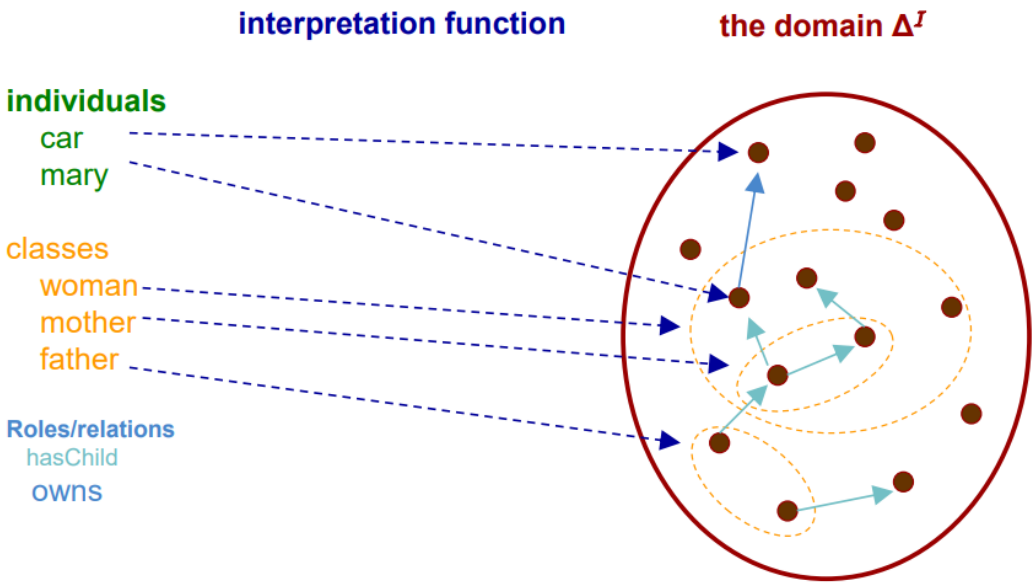

Figure 7: DL semantics

2.5 How to Build an Ontology

Building an ontology involves several steps, each addressing specific aspects of knowledge representation and organization. This process is iterative and is not strictly linear.

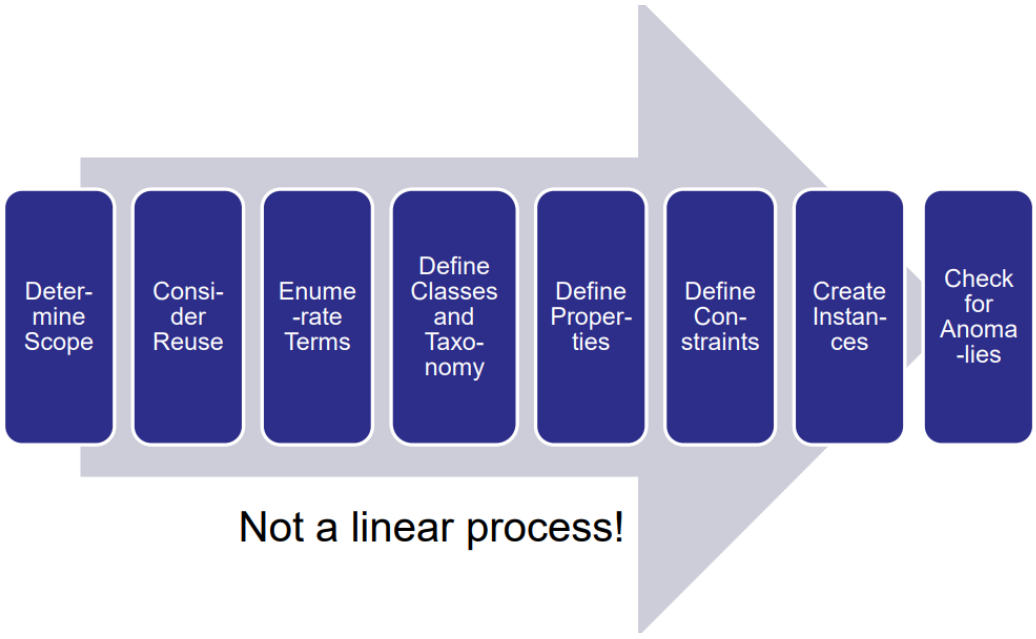

Figure 8: Ontology engineering process

2.5.1 1 - Determine Scope (Competency Questions)

The scope of the ontology should be determined by its intended use and anticipated extensions. Key questions to address include:

- What is the domain that the ontology will cover?
- For what purposes will the ontology be used?
- What types of questions should the ontology answer? (Competency Questions)
- Who will use and maintain the ontology?

Example Competency Questions for a Wine Recommender System:

- Which wine characteristics should I consider when choosing a wine?
- Is Bordeaux a red or white wine?
- Does Cabernet Sauvignon go well with seafood?
- What is the best choice of wine for grilled meat?

2.5.2 2 - Consider Reuse

Reusing existing ontologies saves effort, improves interoperability, and leverages validated ontologies. Sources for reusable ontologies include:

- Protégé Ontology Library (`http://protege.stanford.edu`)
- NCBO Bioportal (`http://bioontology.org`)
- Linked Open Vocabularies (`https://lov.linkeddata.es`)

2.5.3 3 - Enumerate Terms

Write down all relevant terms expected to appear in the ontology. This includes:

- **Nouns**: Basis for class names (e.g., wine, grape, winery).
- **Verbs or Verb Phrases**: Basis for property names (e.g., hasColor, madeFrom).

Examples for a Wine Ontology:

- Terms: wine, grape, winery, region, sugar content.
- Properties: hasColor, locatedIn, madeFrom.

2.5.4 4 - Define Classes and a Taxonomy

Classes represent concepts in the domain and are organized into a taxonomic hierarchy:

- A class is a collection of entities with similar properties (e.g., red wine, winery).
- Subclasses inherit properties from their superclasses.

Example:

- *Red Wine* is a subclass of *Wine*.
- Every instance of *Red Wine* is also an instance of *Wine*.

2.5.5 5 - Define Properties

Properties describe:

- **Attributes** of instances (e.g., color, sugar content).
- **Relationships** between classes (e.g., Wine *hasMaker* Winery).

Properties should:

- Be specified in the highest possible class in the hierarchy.
- Follow domain (parent class) and range (child class) rules.

2.5.6 6 - Define Constraints

Constraints refine the ontology by adding logical rules:

- **Cardinality**: Specifies the number of values a property can have (e.g., each wine has exactly one maker).
- **Existential Restrictions**: Ensures that at least one property exists with a specified value (e.g., wines are located in regions).
- **Universal Restrictions**: Ensures all values of a property are of a certain type (e.g., wines can only be made in wineries).
- **Property Characteristics**: Includes symmetry, transitivity, inverse properties, and functional values.

Examples:

- Wine $\sqsubseteq \geq$1madeFrom.Grape
- Wine $\sqsubseteq \leq$1hasMaker

2.5.7 7 - Create Instances

Instances represent individual entities in the domain:

- The class becomes the direct type of the instance.
- Instances inherit properties and constraints from their class hierarchy.
- Property values assigned to instances must conform to constraints.

Example for a Wine Ontology:

- *Chateau Margaux* is an instance of *Wine*.
- *Chateau Margaux hasMaker Margaux Winery.*

2.5.8 8 - Check Anomalies

Use the formal semantics of the ontology to:

- Validate the model:

  - Check for consistency.
  - Ensure satisfiability of concepts and properties.
- Derive additional knowledge:
  - Automatically classify instances.
  - Infer new relationships or properties.

2.6 Reasoning

Reasoning is one of the key functionalities provided by ontologies due to their formal grounding in logic. It enables the inference of new knowledge based on already declared information. Reasoning is performed using specialized software called reasoners or inference engines.

2.6.1 Capabilities of Reasoning with Ontologies

- **Consistency Checking**: Ensures that the ontology model is free from logical contradictions.
- **Class Inference**: Discovers relationships between classes that were not explicitly declared.
- **Instance Inference**: Determines class membership of instances based on defined relationships and constraints.

2.6.2 Consistency Checking

Consistency checking ensures that the ontology does not contain logical errors:

- Example:
  - Declared: Animal $\sqsubseteq \neg$Plant
  - Declared: Plant(myAlgae)
  - Inferred: Animal(myAlgae)
  - Result: An inconsistency because myAlgae cannot be both an Animal and a Plant.

2.6.3 Satisfiability Checking

Satisfiability checking identifies concepts or classes that cannot possibly have any instances:

- Example:
  - Declared: Algae $\sqsubseteq$ Plant, Animal $\sqsubseteq \neg$Plant, Algae $\sqsubseteq$ Animal
  - Result: The class Algae is unsatisfiable because it cannot belong to both Animal and Plant simultaneously.

2.6.4 Class Inference

Class inference discovers new relationships among classes based on given knowledge:

- Example:
  - Declared: Carnivore $\sqsubseteq$ Animal $\sqcap \forall$eats.Animal
  - Declared: Cat $\sqsubseteq$ Animal $\sqcap \forall$eats.Mouse, Mouse $\sqsubseteq$ Animal
  - Inferred: Cat $\sqsubseteq$ Carnivore

2.6.5 Instance Inference

Instance inference identifies class membership for specific entities:

- Example:
  - Declared: hasPet(Person, Animal), PetOwner $\sqsubseteq$ Person $\sqcap \exists$hasPet.Animal
  - Declared: Person(Pete), Animal(Spike), hasPet(Pete, Spike)
  - Inferred: PetOwner(Pete)

2.6.6 Class + Instance Inference

Combining class and instance inference allows the discovery of both new classes and instance memberships:

- Example:
  - Declared:
    - hasPet(Person, Animal)
    - PetOwner $\sqsubseteq$ Person $\sqcap \exists$hasPet.Animal
    - PetLover $\sqsubseteq$ Person$\sqcap >$ 3hasPet.Animal
  - Declared:
    - Person(Pete), Animal(Tom), Animal(Jerry), Animal(Spike)
    - hasPet(Pete, Spike), hasPet(Pete, Tom), hasPet(Pete, Jerry)
    - $\{Spike\} \sqsubseteq \neg\{Tom, Jerry\}$
  - Inferred:
    - PetOwner(Pete)
    - PetLover(Pete)

Reasoning enables powerful, logic-based conclusions to be drawn from the ontology, enriching both its usability and reliability.

3 Semantic Web, RDF, RDFS, and OWL

3.1 The Semantic Web

The Semantic Web represents an extension of the traditional web, aiming to enable machines to understand and process data in a way that is closer to human reasoning. It focuses on the meaningful interconnection of data to support better knowledge representation, information retrieval, and decision-making.

3.1.1 Key Concepts and Foundations

- **Linked Data:** The Semantic Web is built on the principle of Linked Data, which connects data across different resources using structured formats and qualified links.
  - Links between *things/entities* rather than just documents.
  - Knowledge is *machine-readable*, enabling automated reasoning.
  - Links are qualified to define relationships (e.g., `dbo:city` or `owl:sameAs`).
- **Comparison with the Web of Documents:**
  - The Web of Documents primarily links human-readable pages accessed via browsers.
  - The Web of Data (Semantic Web) links machine-readable entities accessed by programs and agents.
- **Scientific Perspectives:**
  - As emphasized by Sir Tim Berners-Lee: "The more things you have to connect together, the more powerful it is."
  - Decentralized databases underpin this ecosystem, supporting robust knowledge sharing and reasoning.

3.1.2 Semantic Web Language Design Principles

The design of the Semantic Web is governed by specific principles that enable flexibility and interoperability:

AAA Slogan: On the Semantic Web, "Anyone can say Anything about Any topic." This principle highlights the openness of the web, allowing diverse sources to describe and link entities without centralized control.

Non-unique Naming Assumption:

- The same entity may have multiple identifiers (URIs), reflecting its description by different sources.
- Explicit relationships such as `owl:sameAs` are necessary to state that two URIs refer to the same entity.
- Disjointness must also be specified explicitly when entities are distinct.

Open World Assumption (OWA):

- Missing information is not treated as negative information.
- The Semantic Web assumes incomplete knowledge, enabling reasoning over partial data.
- For example:
  - If `likes(PersonA, DrinkB)` is asserted, the OWA does not infer `not likes(PersonA, DrinkC)`.
  - Instead, it concludes `don't know` whether `PersonA` likes `DrinkC`.
- This contrasts with the Closed World Assumption (CWA), where missing information is treated as false.

3.1.3 Benefits of Semantic Web Principles

- Enables a flexible and decentralized approach to knowledge representation.
- Facilitates reasoning and integration of data from disparate sources.
- Supports robust applications in fields like knowledge graphs, data interoperability, and intelligent agents.

3.1.4 Technological Foundations

The Semantic Web leverages existing web technologies to achieve its goals. They are the bottom layer of the Semantic Web Technology stack, which can be seen in 9.

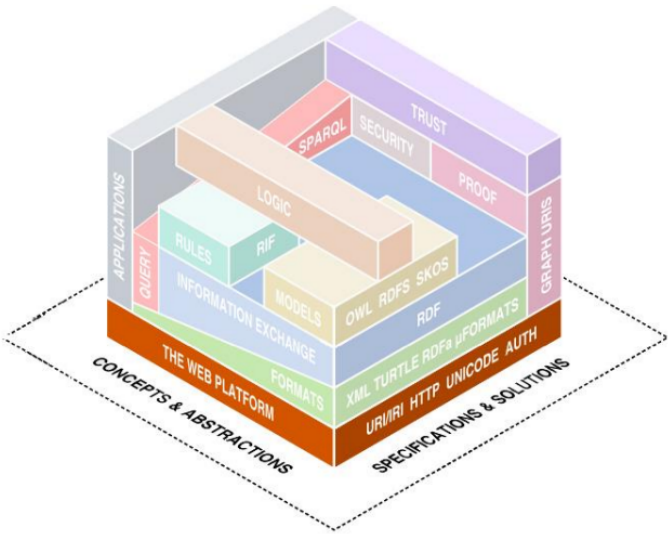

Figure 9: Semantic Web Stack

The technologies used are:

- **TCP/IP:** Facilitates data transfer across networks.
- **HTTP:** Enables client-server communication using a request/response model.

- **HTML and XML:**
  - HTML structures and displays web content.
  - XML provides a flexible markup framework for defining custom data formats.
- **URIs and IRIs:** Identifiers for resources on the web.
  - **URI Types:**
    - Uniform Resource Name (URN): Persistent, location-agnostic identifiers.
    - Uniform Resource Locator (URL): Specifies access mechanisms for resources.
  - **IRI:** An internationalized extension of URI supporting Unicode characters.

3.1.5 Applications and Use Cases

- **Killer Applications:**
  - Intelligent agents retrieving, analyzing, and negotiating information.
  - Scheduling and coordination for multiple stakeholders (e.g., treatments or services).
- **Ontology and Knowledge Representation:**
  - Provides structured models to represent domains of knowledge.
  - Enhances the interoperability and reasoning capabilities of intelligent systems.

3.1.6 Challenges and Evolution

- The Semantic Web is still evolving, requiring:
  - Better adoption of Linked Data principles.
  - Tools for creating, managing, and consuming semantic data.
- Continues to build on the foundational technologies of the traditional web.

3.2 RDF

The Resource Description Framework (RDF) is a W3C standard designed to describe resources on the web in a structured and machine-readable way. It is foundational to the Semantic Web and provides a framework for knowledge representation and sharing across diverse systems.

3.2.1 Overview of RDF

RDF was developed in the late 1990s, with its final W3C recommendation (RDF 1.1) released in 2004. It uses a graph-based data model that formalizes semantics, making it accessible to machines. RDF expresses knowledge as a collection of statements, where each statement is represented as an RDF triple.

An RDF triple consists of:

- **Subject:** The resource being described, identified by a URI.

- **Predicate:** The relationship or property linking the subject to the object, also identified by a URI.
- **Object:** The value or related resource, which can be a URI or a literal.

3.2.2 RDF Graph Model

RDF statements naturally form a directed labeled graph, where:

- Nodes represent resources (subjects or objects).
- Arcs represent predicates, connecting subjects to objects.

For instance, the RDF triple:

```
<http://example.org/person/John>
<http://example.org/property/worksIn>
<http://example.org/resource/ProjectX>
```

is visualized as a graph:

$$\text{John} \xrightarrow{\text{worksIn}} \text{ProjectX}.$$

The object of one statement can act as the subject of another, enabling the integration of multiple graphs.

3.2.3 RDF Serialization Formats

RDF provides multiple serialization formats for different use cases, including machine communication, human readability, and ease of implementation. Common formats include RDF/XML, N-Triples, Turtle, and JSON-LD.

RDF/XML RDF/XML is one of the earliest serialization formats, suitable for inter-machine communication. It uses XML to describe RDF statements. An example:

```
<rdf:RDF xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-ns#">
  <rdf:Description rdf:about="http://example.org/person/John">
    <worksIn rdf:resource="http://example.org/resource/ProjectX" />
  </rdf:Description>
</rdf:RDF>
```

N-Triples N-Triples is a simple, line-based format where each statement is terminated by a period. Example:

```
<http://example.org/person/John>
<http://example.org/property/worksIn>
<http://example.org/resource/ProjectX> .
```

Turtle Turtle (Terse RDF Triple Language) is a human-readable serialization format and a subset of N3. It allows shorthand notations for repeated subjects or predicates. Example:

```
@prefix ex: <http://example.org/> .

ex:John
    ex:worksIn ex:ProjectX ;
    ex:hasSkill "Programming" .
```

Turtle also supports data types and language tags for literals. Example:

```
ex:John ex:age "27"^^xsd:integer ;
         ex:name "John"@en .
```

3.2.4 RDF Literals and Datatypes

RDF supports two types of literals:

- **Plain Literals:** Text values with an optional language tag, e.g., `"Hello World"@en`.
- **Typed Literals:** Text values paired with a datatype URI, e.g., `"27"8sd:integer`.

The datatypes are based on XML Schema, defining value spaces, lexical spaces, and mappings between them.

3.2.5 RDF in Practice

RDF facilitates the integration of knowledge by enabling the merging of multiple graphs. For example, consider two datasets:

- Dataset A states `John worksIn ProjectX`.
- Dataset B states `ProjectX isIn NewYork`.

By combining these graphs, we infer that `John worksIn NewYork`, demonstrating RDF's power to create a web of interconnected knowledge.

3.2.6 Conclusion

RDF is the backbone of the Semantic Web, providing a standard way to describe and link data. Its flexible model and variety of serialization formats ensure its adaptability for various applications, from knowledge graphs to linked data publishing.

3.3 Advanced RDF

Advanced RDF concepts extend the basic principles of RDF to accommodate more complex data structures, unnamed resources, and metadata about statements. These features support nuanced data modeling, enhance flexibility, and address specific challenges in RDF knowledge representation.

3.3.1 Structured Values

RDF enables the representation of structured values, such as addresses, by describing the "aggregated thing" (e.g., an address) as a separate resource. Statements about this new resource capture its individual components, such as street, city, state, and postal code.

Example in Triples Notation:

```
exstaff:85740 exterms:address exaddressid:85740 .
exaddressid:85740 exterms:street "Favoritenstrasse 9-11/188" .
exaddressid:85740 exterms:city "Vienna" .
exaddressid:85740 exterms:state "Vienna" .
exaddressid:85740 exterms:postalCode "1040" .
```

Example in Turtle:

```
exstaff:85740 exterms:address exaddressid:85740 .
exaddressid:85740 exterms:street "Favoritenstrasse 9-11/188" ;
              exterms:city "Vienna" ;
              exterms:state "Vienna" ;
              exterms:postalCode "1040" .
```

3.3.2 Blank Nodes

Blank nodes are unnamed resources represented in RDF. They are useful for describing resources without assigning URIs, grouping related information, or representing n-ary relationships. However, they pose challenges for reasoning and are discouraged in Linked Data, though they remain widely used.

Example Using Blank Nodes:

```
exstaff:85740 exterms:address _:johnaddress .
_:johnaddress exterms:street "1501 Grant Avenue" .
_:johnaddress exterms:city "Bedford" .
_:johnaddress exterms:state "Massachusetts" .
_:johnaddress exterms:postalCode "01730" .
```

3.3.3 Reification

Reification allows making statements about other statements, such as metadata, provenance, or trust. However, it introduces complexity and potential for infinite recursion or cycles.

Standard Reification Example:

```
:Max :says _:s1 .
_:s1 rdf:type rdf:Statement .
_:s1 rdf:subject :Max .
_:s1 rdf:predicate :likes .
_:s1 rdf:object :StarTrek .
```

Alternative approaches to reification include singleton properties, named graphs, and RDF-star (RDF*). Each method has trade-offs in terms of space efficiency, query performance, and system support.

3.3.4 RDF Data Structures: Containers and Collections

RDF supports two primary data structures:

- **Containers:** Open lists that allow the addition of new entries. Examples include `rdf:Bag`, `rdf:Seq`, and `rdf:Alt`.
- **Collections:** Closed lists where entries are fixed and cannot be extended.

Example of an RDF Collection in Turtle:

```
ex:fruits rdf:type rdf:List ;
          rdf:first "Apple" ;
          rdf:rest ( "Banana" "Cherry" rdf:nil ) .
```

3.3.5 RDF Vocabulary

The RDF vocabulary includes predefined classes and properties:

- **Classes:** `rdf:XMLLiteral`, `rdf:Property`, `rdf:Statement`, `rdf:Alt`, `rdf:Bag`, `rdf:Seq`, `rdf:List`.
- **Properties:** `rdf:type`, `rdf:first`, `rdf:rest`, `rdf:value`, `rdf:subject`, `rdf:predicate`, `rdf:object`.

3.3.6 RDF-star and RDF*

RDF-star introduces nested triples as first-class citizens, simplifying the representation of statements about statements. For example:

```
:Alice :says <<:Bob :likes :StarTrek>> .
```

This approach is space-efficient and expressive but is not yet standardized across all triple stores.

3.3.7 Conclusion

Advanced RDF extends the basic RDF model to handle structured data, metadata, and complex relationships. By providing flexible tools for modeling nuanced scenarios, RDF supports a wide range of applications in the Semantic Web and Linked Data ecosystems.

3.4 RDFS (RDF Schema)

RDF Schema (RDFS) is an extension of RDF that introduces a vocabulary for defining the structure and relationships of RDF data. It provides basic semantic constructs to enable inference and organize RDF data into hierarchies, thus enhancing its expressivity.

3.4.1 Purpose of RDFS

RDFS serves two main purposes:

1. **Nomination:**
    - Defines the "types" (i.e., classes) of things about which we make assertions.

- Specifies the properties that can act as predicates in these assertions to capture relationships.

2. **Inference:**
   - Allows reasoning over data to infer additional knowledge that is implicit based on the provided assertions.

3.4.2 Main Constructs of RDFS

RDFS introduces several key constructs to define classes, properties, and their relationships.

Classes:

- `rdfs:Resource`: The superclass of all resources in RDF.
- `rdfs:Class`: Declares a resource as a class (type or category) for other resources.
- `rdfs:Literal`: Represents literal values such as strings and numbers.
- `rdfs:Datatype`: A class of datatypes (e.g., `xsd:string`, `xsd:integer`), which is both an instance of and a subclass of `rdfs:Class`.

Properties:

- `rdfs:subClassOf`: Defines class hierarchies where properties of a superclass are inherited by its subclasses.
- `rdfs:subPropertyOf`: Defines property hierarchies where related resources by a subproperty are also related by its superproperty.
- `rdfs:domain`: Restricts the scope of a property to specific classes.
- `rdfs:range`: Restricts the range of values a property can have.
- `rdfs:comment`: Provides a human-readable description of a resource.
- `rdfs:seeAlso`: Indicates resources that provide additional information.
- `rdfs:isDefinedBy`: Points to a resource that defines the subject.

3.4.3 Example of Class Hierarchies

The following example demonstrates the use of `rdfs:subClassOf` to define hierarchies:

RDFS Example in Turtle:

```
@prefix ex: <http://example.org/> .
@prefix rdfs: <http://www.w3.org/2000/01/rdf-schema#> .

ex:Person a rdfs:Class .
ex:Author rdfs:subClassOf ex:Person .
ex:Reader rdfs:subClassOf ex:Person .
```

```
ex:Frank a ex:Author .
ex:Lynda a ex:Reader .
ex:Frank ex:communicatesTo ex:Lynda .
```

From this data, an RDFS reasoner can infer:

- `ex:Frank` is an instance of `ex:Person`.
- `ex:Lynda` is an instance of `ex:Person`.

3.4.4 Domain and Range Restrictions

The `rdfs:domain` and `rdfs:range` properties restrict the applicability and type of properties.

Example in Turtle:

```
@prefix mo: <http://purl.org/ontology/mo/> .
@prefix foaf: <http://xmlns.com/foaf/0.1/> .
@prefix rdfs: <http://www.w3.org/2000/01/rdf-schema#> .

mo:member rdfs:domain mo:MusicGroup .
mo:member rdfs:range foaf:Agent .

mo:TheBeatles mo:member foaf:PaulMcCartney .
```

From this data, the following can be inferred:

- `mo:TheBeatles` is an instance of `mo:MusicGroup`.
- `foaf:PaulMcCartney` is an instance of `foaf:Agent`.

3.4.5 RDFS Vocabulary

The RDFS vocabulary expands RDF with the following classes and properties:

- **Classes:**
  - `rdfs:Resource`, `rdfs:Class`, `rdfs:Literal`, `rdfs:Datatype`, `rdfs:Container`, `rdfs:List`
- **Properties:**
  - `rdfs:subClassOf`, `rdfs:subPropertyOf`, `rdfs:domain`, `rdfs:range`, `rdfs:comment`, `rdfs:seeAlso`, `rdfs:isDefinedBy`.

3.4.6 Limitations of RDFS

Despite its utility, RDFS has significant limitations:

- It supports only basic inference and lacks the expressivity for complex reasoning.
- It does not allow for logical expressions beyond membership and basic hierarchies.

3.5 OWL (Web Ontology Language)

The Web Ontology Language (OWL) is a W3C recommendation designed for representing ontologies on the Semantic Web. OWL extends RDF and RDFS, providing a fully-fledged knowledge representation language that incorporates logical constructs and formal semantics. It enables more expressive and complex descriptions of knowledge domains while supporting inferencing to derive implicit knowledge.

3.5.1 Overview and Purpose

OWL addresses the limitations of RDFS by introducing a richer set of constructs and logical operators. Its formal foundation lies in Description Logics (DL), which provide:

- Well-defined semantics for precise reasoning.
- Mechanisms to verify the consistency of knowledge bases.
- Tools to infer implicit knowledge from explicitly defined statements.
- Computationally manageable reasoning processes.

OWL ontologies are typically expressed in RDF syntax, enabling easy integration and sharing on the Semantic Web.

3.5.2 Extending RDFS

OWL extends RDFS in several significant ways, including:

- Logical expressions such as `AND`, `OR`, `NOT`.
- Equality and inequality of classes and individuals.
- Local properties with domain- and range-specific constraints.
- Cardinality constraints, such as specifying the number of relationships.
- Symmetric, transitive, and inverse properties.
- Enumerated classes and required/optional properties.

For example, the following OWL statements specify the symmetry of a property:

```
:hasSibling a owl:ObjectProperty ;
            owl:SymmetricProperty .
```

3.5.3 Classes and Individuals

Classes in OWL define sets of individuals and are referred to as "types," "concepts," or "categories." Membership in a class is determined by logical descriptions rather than names. OWL defines two special classes:

- `owl:Thing`: The universal class that includes all individuals.
- `owl:Nothing`: The empty class containing no individuals.

Defining Classes and Individuals:

```
:Book a owl:Class .
:NineteenEightyFour a :Book .
:FrankSmith a owl:NamedIndividual .
```

3.5.4 Properties

OWL properties are binary relations between individuals or between individuals and data values. They come in two main types:

- **Object Properties:** Relate individuals to other individuals.
- **Datatype Properties:** Relate individuals to data values.

Examples of Object and Datatype Properties:

```
:author a owl:ObjectProperty ;
        rdfs:domain :Book ;
        rdfs:range :Writer .

:publicationYear a owl:DatatypeProperty ;
                 rdfs:domain :Book ;
                 rdfs:range xsd:integer .
```

Object properties can have characteristics such as transitivity, symmetry, and inverses:

```
:hasParent a owl:ObjectProperty ;
           owl:TransitiveProperty .
:hasBrother owl:SymmetricProperty .
:hasSpouse owl:inverseOf :isSpouseOf .
```

3.5.5 Class Hierarchies and Inference

OWL allows the creation of class hierarchies through subclass relationships, supporting reasoning to infer implicit relationships. For example:

```
:Novel a owl:Class ;
       rdfs:subClassOf :Book .

:Book a owl:Class ;
       rdfs:subClassOf :Work .

:Work a owl:Class .
```

From the above definitions, an OWL reasoner can infer that:

- `:Novel` is a subclass of `:Work`.
- Any individual of `:Novel` is also an individual of `:Work`.

OWL also supports the declaration of disjoint classes and equivalence:

```
:Book owl:disjointWith :Writer .
:Writer owl:equivalentClass :Author .
```

3.5.6 Advanced Constructs

OWL supports advanced constructs such as:

- **Cardinality:** Specifies the number of relationships an individual can have. For example:

```
:Person a owl:Class ;
        owl:equivalentClass [
            a owl:Restriction ;
            owl:onProperty :hasChild ;
            owl:minQualifiedCardinality "1"^^xsd:nonNegativeInteger ;
            owl:onClass :Child
        ] .
```

- **Enumerated Classes:** Defines classes by enumerating their members:

```
:PrimaryColors a owl:Class ;
               owl:oneOf (:Red :Blue :Yellow) .
```

- **Property Restrictions:** Enforces constraints on property values:

```
:Person a owl:Class ;
        owl:equivalentClass [
            a owl:Restriction ;
            owl:onProperty :hasAge ;
            owl:allValuesFrom xsd:integer
        ] .
```

3.5.7 Combining TBox and ABox

OWL integrates the TBox (terminology, or schema) and ABox (assertions, or instance data) into a unified framework. For instance:

```
:Book a owl:Class .
:Writer a owl:Class .
:NineteenEightyFour a :Book ;
                    :author :GeorgeOrwell ;
                    :publicationYear 1948 .
```

3.5.8 Inference and Reasoning

OWL reasoners leverage Description Logics to infer new knowledge from existing assertions. For example:

- Given `:Poet rdfs:subClassOf :Writer` and `:Writer owl:equivalentClass :Author`, a reasoner can infer `:Poet rdfs:subClassOf :Author`.

- Individuals can be related or distinguished:

```
:NineteenEightyFour owl:sameAs :ARX012345 .
:ARX012345 owl:differentFrom :ARX0123456 .
```

3.6 Advanced OWL

Advanced OWL concepts extend the foundational constructs to provide a more expressive framework for representing complex relationships, restrictions, and logical constructs in ontologies. These features enable nuanced reasoning and interoperability for knowledge representation on the Semantic Web.

3.6.1 Disjunctive Properties

Disjunctive properties ensure that two individuals cannot be related through both properties simultaneously. OWL provides constructs for declaring disjoint properties.

Example of Disjoint Properties:

```
:hasParent a owl:ObjectProperty ;
           owl:propertyDisjointWith :hasChild .
```

For multiple disjunctive properties, OWL provides a shortcut:

```
[] rdf:type owl:AllDisjointProperties ;
   owl:members (:hasParent :hasChild :hasGrandchild) .
```

3.6.2 Transitive Properties

A transitive property enables reasoning over chains of relationships. If a relationship exists between `A` and `B`, and between `B` and `C`, it can be inferred that the relationship exists between `A` and `C`.

Example of a Transitive Property:

```
:isPublishedBefore a owl:ObjectProperty ;
                   owl:TransitiveProperty ;
                   rdfs:domain owl:Book ;
                   rdfs:range owl:Book .

:AnimalFarm a owl:Book ;
            :isPublishedBefore :NineteenEightyFour .

:BraveNewWorld a owl:Book ;
               :isPublishedBefore :AnimalFarm .
```

From this, an OWL reasoner can infer:

```
:BraveNewWorld :isPublishedBefore :NineteenEightyFour .
```

3.6.3 Closed Classes (Nominals)

OWL allows the definition of closed classes using the `owl:oneOf` construct. This restricts membership in the class to explicitly enumerated individuals.

Example of Closed Classes:

```
:Novel a owl:Class ;
       owl:oneOf (:AnimalFarm :NineteenEightyFour) .

:AnimalFarm a :Novel .
:NineteenEightyFour a :Novel .
```

This states that only `:AnimalFarm` and `:NineteenEightyFour` are members of the `:Novel` class.

3.6.4 Property Restrictions

OWL supports property restrictions to define complex classes based on relationships. Restrictions include:

- `owl:hasValue`: Restricts a property to a fixed value.
- `owl:allValuesFrom`: Specifies that all values of a property must belong to a specific class (universal quantification).
- `owl:someValuesFrom`: Specifies that at least one value of a property must belong to a specific class (existential quantification).
- `owl:cardinality`, `owl:minCardinality`, `owl:maxCardinality`: Restrict the number of relationships a property can have.

Example of Universal Restriction:

```
:VegetarianPizza a owl:Class ;
                 rdfs:subClassOf [
                     a owl:Restriction ;
                     owl:onProperty :hasTopping ;
                     owl:allValuesFrom :VegetarianTopping
                 ] .
```

Example of Existential Restriction:

```
:Reader a owl:Class ;
        rdfs:subClassOf [
            a owl:Restriction ;
            owl:onProperty :reads ;
            owl:someValuesFrom :Book
        ] .
```

Example of Cardinality Restriction:

```
:Tetralogy a owl:Class ;
           rdfs:subClassOf [
               a owl:Restriction ;
               owl:onProperty :hasVolumes ;
               owl:cardinality 4
           ] .
```

3.6.5 Property Characteristics and Relationships

OWL provides constructs for defining advanced property characteristics:

- `owl:SymmetricProperty`: A property is symmetric if the relationship is bidirectional (e.g., `isSiblingOf`).
- `owl:TransitiveProperty`: A property is transitive if it holds over chains of relationships (e.g., `isPartOf`).
- `owl:FunctionalProperty`: A property is functional if an individual can have at most one value for it (e.g., `hasBirthDate`).
- `owl:InverseFunctionalProperty`: A property is inverse functional if its inverse is functional (e.g., `isBirthMotherOf`).
- `owl:AsymmetricProperty`: A property is asymmetric if the inverse relationship cannot hold (e.g., `isLeftOf`).
- `owl:ReflexiveProperty`: A property is reflexive if it always relates an individual to itself (e.g., `isEqualTo`).
- `owl:IrreflexiveProperty`: A property is irreflexive if no individual can relate to itself (e.g., `isParentOf`).

Example of a Symmetric Property:

```
:isSiblingOf a owl:ObjectProperty ;
             owl:SymmetricProperty .
```

Example of an Inverse Property:

```
:hasSpouse a owl:ObjectProperty ;
           owl:inverseOf :isSpouseOf .
```

3.6.6 Combining Restrictions

OWL enables the combination of restrictions to define complex classes. For example:

```
:VegetarianPizza a owl:Class ;
                 rdfs:subClassOf [
                     a owl:Restriction ;
                     owl:onProperty :hasTopping ;
```

```
        owl:someValuesFrom :VegetarianTopping
    ] ;
    rdfs:subClassOf [
        a owl:Restriction ;
        owl:onProperty :hasTopping ;
        owl:allValuesFrom :VegetarianTopping
    ] .
```

This defines `:VegetarianPizza` as a class where all toppings are vegetarian and at least one topping is specified.

4 SPARQL

SPARQL (SPARQL Protocol and RDF Query Language) is the W3C-standardized query language for RDF (*Resource Description Framework*). It enables applications to retrieve, manipulate, and update RDF data by expressing queries that match graph patterns. SPARQL queries operate over one or multiple RDF graphs, which are essentially sets of subject–predicate–object triples. In the sections below, we will explore the core ideas of SPARQL, from basic queries and solution modifiers to advanced features like optional patterns, federated queries, and SPARQL 1.1 updates.

4.0.1 Overview and RDF Graphs

An RDF graph is a collection of statements in the form of triples. Each triple consists of a subject, a predicate, and an object, which can be IRIs (Internationalized Resource Identifiers), blank nodes, or literals. SPARQL treats such graphs as the data source on which pattern matching is performed. A key point of working with SPARQL is understanding that the query engine inspects these triples and returns results whenever a subset of the graph matches the query pattern.

In practice, SPARQL can query one or more named graphs, providing flexibility in how data is partitioned. A default graph can be declared, or multiple named graphs can be accessed. This allows queries to pull together data from different parts of the knowledge base or even from external datasets.

4.0.2 SPARQL Query Forms

SPARQL supports four primary query forms: `SELECT`, `ASK`, `DESCRIBE`, and `CONSTRUCT`. Each query form has its own use case. The `SELECT` query returns variable bindings in a tabular structure, serving as the most common way to retrieve data. When an application needs to check for the existence of a certain pattern, an `ASK` query is appropriate, as it returns a simple boolean `true` or `false`.

For exploration of unfamiliar data, `DESCRIBE` queries can be used: they return additional statements considered relevant by the SPARQL endpoint about resources matching the query. Lastly, `CONSTRUCT` queries transform the original RDF graph into a new RDF graph. They allow you to specify a *template* in which matching variables are substituted with actual data, thus producing new triples. This is especially useful for reformatting data from one vocabulary to another or for materializing inferred statements for later use.

4.0.3 Basic Graph Patterns

The core mechanism of a SPARQL query is graph pattern matching. A set of triple patterns, enclosed in braces {}, specifies the structure that needs to be matched in the data. Each triple pattern can contain variables (denoted with a question mark, such as `?album` or `?track`), IRIs, or literals. The SPARQL processor returns solutions for all possible ways those triple patterns can match the RDF dataset.

For example:

```
PREFIX dbpedia: <http://dbpedia.org/resource/>
PREFIX foaf:    <http://xmlns.com/foaf/0.1/>
SELECT ?album
WHERE {
```

```
  dbpedia:The_Beatles foaf:made ?album .
}
```

matches all triples where `dbpedia:The_Beatles` (the subject) and `foaf:made` (the predicate) appear, and any object becomes bound to the variable `?album`.

4.0.4 Solution Modifiers: Filtering, Ordering, and Aggregation

After extracting candidate solutions, it is often necessary to refine them. SPARQL solution modifiers accomplish this. For instance, `FILTER` allows you to limit solutions based on conditions, such as numeric comparisons or string patterns. Meanwhile, `ORDER BY` reorders results according to a given variable, and `LIMIT` and `OFFSET` let you retrieve only a portion of the overall result set.

Aggregates such as `COUNT`, `SUM`, `AVG`, `MIN`, and `MAX`, combined with `GROUP BY`, enable straightforward data analytics within SPARQL. You can also use `HAVING` clauses to further filter groups based on the computed aggregate values. For example, computing the total duration of all tracks in an album is as simple as grouping tracks by album and applying a `SUM`.

4.0.5 Advanced Query Patterns: UNION, OPTIONAL, and Subqueries

Beyond basic patterns, SPARQL includes more advanced constructs. The `UNION` keyword performs a logical disjunction, matching data that satisfies one pattern or another (or both). This is essential for queries that must gather data from multiple possible paths in the graph.

The `OPTIONAL` keyword is used when certain parts of the data may be missing. If an `OPTIONAL` pattern exists in the data, it is included in the result; if not, the solution remains valid but with a missing variable for that pattern. This is particularly useful when dealing with incomplete or heterogeneous data.

Subqueries can also be nested inside a larger `SELECT`, `CONSTRUCT`, or other query forms. They allow for more complex logic: for instance, computing an intermediate result, grouping it, and then using it in an outer query. With subqueries, you can filter or aggregate at an inner level before passing results along to the outer query.

4.0.6 Federated Queries

SPARQL also supports the notion of federated queries, allowing you to query multiple endpoints in a single statement. By using the `SERVICE` keyword, you can direct certain parts of your query to remote SPARQL endpoints. This enables data retrieval from diverse sources across the web of Linked Data, seamlessly integrating them into one coherent result set. A typical use case might involve fetching information about movies from one endpoint and cross-referencing it with actor data from another.

4.0.7 Entailment Regimes

One of the key advantages of RDF is its schema and inference capabilities. In SPARQL, reasoners can implement various entailment regimes (e.g., RDFS or OWL-based reasoning) to infer new facts beyond those explicitly stated. For example, if `mo:MusicGroup` is declared a subclass of `mo:MusicArtist`, then an individual typed as a `mo:MusicGroup` will also be considered a `mo:MusicArtist` in queries, provided the store or endpoint supports reasoning. These inferred facts can significantly enrich query results and reveal deeper relationships in the data.

4.0.8 SPARQL 1.1 Updates

Initially, SPARQL 1.0 provided powerful querying features but no direct mechanism to change RDF data. SPARQL 1.1 introduced a suite of update operations. `INSERT DATA` and `DELETE DATA` enable adding or removing specified triples, while the combined `DELETE/INSERT` pattern is ideal for modifying existing data in a single step. These updates typically appear in a `WHERE` block that selects which data to remove and how to transform it for insertion.

Additionally, SPARQL 1.1 offers graph-level operations such as `CREATE`, `CLEAR`, and `DROP` to manage named graphs in a triple store, as well as `LOAD` to import data from external files. Finally, operations such as `MOVE`, `COPY`, and `ADD` facilitate graph-level data management by transferring triples between named graphs.

5 SHACL

The Shapes Constraint Language (SHACL) is a W3C standard[1] designed for validating and describing constraints on RDF graphs. These constraints capture how data should be structured and related, thereby increasing trust in the quality and consistency of the underlying information. SHACL provides a rich vocabulary for defining and organizing shapes, which can specify constraints at the node level and at the property level. When a dataset is validated against these shapes, a validation report is produced, indicating any violations or potential issues.

5.0.1 Overview of SHACL

At its core, SHACL consists of two types of RDF graphs: a *data graph* and a *shapes graph*. The data graph contains the actual assertions about entities and their relationships, while the shapes graph describes how these entities are expected to appear. During validation, nodes in the data graph are checked against the shapes in the shapes graph, and any constraint violations are recorded in the final validation report.

The shapes graph itself is composed of one or more shapes. These shapes can specify conditions such as the number of allowed values for a given property, the type of those values, or logical combinations of constraints. Since shapes and constraints are expressed in RDF, the same data modeling environment used for domain data can also describe the validation rules.

5.0.2 Targets and Focus Nodes

Central to the SHACL validation process is the concept of *targets*, which determine which nodes in the data graph need to satisfy a given shape. These targeted nodes are called *focus nodes*. SHACL provides various kinds of targets. In practice, one might specify a target class so that all individuals of that class are validated against the shape, or even select a specific node directly. Other target types include all subjects of a certain property or all objects of a certain property. Once the SHACL processor identifies the focus nodes from the targets, it applies the relevant constraints to those nodes and checks for compliance.

Example. Suppose we have a shape named `ex:PersonShape` that is intended for individuals of type `ex:Person`. By declaring

```
ex:PersonShape
  a sh:NodeShape ;
  sh:targetClass ex:Person .
```

all nodes in the data graph that are of type `ex:Person` become focus nodes and must fulfill the shape's constraints.

5.0.3 Node Shapes and Property Shapes

SHACL distinguishes between two general categories of shapes: *node shapes* and *property shapes*. A node shape specifies constraints that must be met by the focus node itself, while a property shape focuses on the values of a particular property path from the focus node.

[1] `https://www.w3.org/TR/shacl/`

A typical shape can contain both node-level requirements and property-level constraints. For instance, one might say that all individuals of `ex:Person` must have a minimum of one `ex:ssn` value and that `ex:ssn` must not appear more than once per person. In SHACL, this rule can be written by embedding a *property shape* inside the node shape:

```
ex:PersonShape
  a sh:NodeShape ;
  sh:targetClass ex:Person ;
  sh:property [
    a sh:PropertyShape ;
    sh:path ex:ssn ;
    sh:minCount 1 ;
    sh:maxCount 1
  ] .
```

Here, `sh:minCount` and `sh:maxCount` are examples of *cardinality constraints*, ensuring that each person node has at least one and at most one value for the property `ex:ssn`.

5.0.4 Core Constraints in SHACL

SHACL core constraints cover a wide variety of common data validation needs, including value type checking, range restrictions, and string pattern constraints. These may be applied individually or combined in more complex ways using logical operators. Some common constraints include:

- `sh:maxCount`, `sh:minCount` for specifying the cardinality of a property.
- `sh:maxLength`, `sh:minLength`, `sh:pattern` for string-based constraints.
- `sh:in` for enumerations, restricting property values to a given set.
- `sh:not`, `sh:and`, `sh:or`, `sh:xone` for expressing logical combinations of constraints.

Although these constraints can be listed succinctly, their actual usage in a shapes graph often involves more extensive descriptions, especially when specifying multiple shapes that share properties or when combining constraints via logical operators. An additional mechanism, the `sh:node` constraint, can require that property values themselves conform to another shape, facilitating nested validation.

5.0.5 Practical Observations and Example

Consider a small data graph:

```
ex:Alice  rdf:type   ex:Person .
ex:Alice  ex:ssn     "987-65-432A" .
ex:Bob    rdf:type   ex:Person .
ex:Bob    ex:ssn     "123-45-6789" .
ex:Bob    ex:ssn     "124-35-6789" .
ex:Calvin rdf:type   ex:Person .
ex:Calvin ex:birthDate "1971-07-07"^^xsd:date .
ex:Calvin ex:worksFor ex:UntypedCompany .
```

We might want to ensure that every person has exactly one `ex:ssn` and that those values match a certain pattern. The shape could be extended with a regular expression constraint, for instance:

```
ex:PersonShape
  a sh:NodeShape ;
  sh:targetClass ex:Person ;
  sh:property [
    a sh:PropertyShape ;
    sh:path ex:ssn ;
    sh:maxCount 1 ;
    sh:pattern "^[0-9]{3}-[0-9]{2}-[0-9]{4}$"
  ] .
```

This enforces that the `ex:ssn` property can appear at most once and must match the typical US Social Security Number format. In a validation report, `ex:Alice` would fail the `sh:pattern` check, and `ex:Bob` would fail the `sh:maxCount` check because he has two distinct values for `ex:ssn`.

5.0.6 Improving RDF Quality with SHACL

By systematically applying constraints, SHACL helps identify common data issues, such as missing fields, invalid data formats, or undesired duplications. Organizations can thus use SHACL validation to ensure that their RDF datasets remain consistent with the intended domain model or schema guidelines. When violations occur, the SHACL engine produces detailed information about which shapes or constraints failed, allowing data curators to correct the problems swiftly. Consequently, leveraging SHACL promotes higher data integrity, making it especially valuable in production knowledge graphs where data is integrated from heterogeneous sources.

Moreover, recent community surveys on shape usage highlight that many practitioners create SHACL shapes manually, tailoring constraints to the specific modeling requirements of their domains. Automation tools do exist, but often struggle with data diversity and can produce overly general shapes, which then require considerable refining. As a result, an iterative approach of shape creation, testing, and adjustment is a common practice in real-world settings.

5.0.7 Conclusion

SHACL stands as a robust framework for describing and validating constraints on RDF data. Its mechanism of applying node shapes and property shapes provides a fine-grained approach to data quality checks, covering both syntactic and semantic aspects. By adopting SHACL and carefully curating a shapes graph alongside domain data, knowledge engineers can systematically identify inconsistencies, enforce cardinality limits, and ensure coherence in complex knowledge graphs. As RDF usage continues to expand across various industries and communities, SHACL validation helps maintain trust and reliability in the ever-growing network of linked data.

6 Knowledge Graph Creation

6.1 Introduction

Knowledge graphs integrate data from diverse sources into a coherent, semantically rich representation. Their fundamental building blocks are *entities* (resources) and *relationships* (edges) enriched with metadata, allowing machines and humans to derive context and meaning beyond the raw data itself. A typical challenge in knowledge graph creation is how to transform, map, and publish data—often stored in relational databases, spreadsheets, or JSON APIs—into RDF (Resource Description Framework), the primary data model for knowledge graphs.

One approach to building a knowledge graph is *template-based on-the-fly generation*, where existing web infrastructures dynamically render JSON, HTML, or other front-end representations from back-end databases. By using JSON-LD (JSON for Linked Data), it is possible to seamlessly embed structured semantic information into JSON documents. The added `@context` fields reference established vocabularies (such as `schema.org` or FOAF), aligning local properties with well-known semantic concepts. A browser or script not capable of interpreting RDF can still read the JSON as usual, while an RDF-aware processor or triple store extracts the semantics and stores them as triples. This makes JSON-LD particularly suitable for adding Linked Data to existing RESTful or web-based services without drastic changes in infrastructure.

A complementary strategy involves *mapping and transformation tools*. These tools convert data from formats like CSV, relational tables, or even unstructured text directly into RDF. For relational databases, the W3C-standard `R2RML` (RDB to RDF Mapping Language) provides a declarative mapping of database tables and columns to classes, properties, and individuals in an RDF graph. This workflow ensures a reproducible pipeline: one defines the mapping once, and the tool automatically transforms the data as needed, updating the knowledge graph whenever the source changes.

In practice, organizations and developers often combine both template-based and mapping-based methods. For instance, a web application could use on-the-fly JSON-LD generation for immediate API responses, while background processes or dedicated ETL (Extract–Transform–Load) jobs apply R2RML or related mappings to maintain a consolidated RDF store. Regardless of the chosen method, the underlying goal remains the same: to increase interoperability, enrich the data with domain semantics, and create a scalable infrastructure where diverse datasets come together as a comprehensive knowledge graph.

6.2 Tabular Data to RDF

When creating a knowledge graph, much of the source data often exists in tabular formats such as spreadsheets or CSV files. Traditional table-based data can be rich in information, but it typically lacks the semantic structure and linking conventions required for a knowledge graph. To bridge this gap, a popular solution involves using *OpenRefine*, a tool designed for cleaning, transforming, and reconciling messy data. The end goal is to export the refined data as RDF, thereby aligning it with a chosen vocabulary or ontology.

6.2.1 OpenRefine for Data Preparation

OpenRefine, originally developed by Google (under the name Google Refine), presents a user interface that resembles a spreadsheet application yet operates under a different philosophy. Rather than

manually editing individual cells, OpenRefine applies transformations in bulk. This makes it easier to address common data wrangling tasks, such as:

- Splitting columns that contain composite values (e.g., multiple genres in one cell).
- Converting data types (e.g., converting string representations of dates into machine-readable date formats).
- Normalizing text (e.g., removing extra whitespace or punctuation).

While these tasks can be performed manually in small datasets, OpenRefine's real strength emerges when dealing with larger or more complicated tables. Its transformation steps are recorded in a reproducible script, enabling users to reapply them to different but structurally similar datasets. This *history of operations* can be shared with collaborators or reused on updated versions of the dataset, ensuring consistency in how the data is cleaned and prepared.

6.2.2 Entity Reconciliation

One of the most powerful features in OpenRefine is *entity reconciliation*, which provides a way to map textual identifiers or names in a table to canonical URIs in existing knowledge bases. For instance, you may have a column listing artist names, such as "The Beatles" or "Led Zeppelin." By leveraging an external reconciliation service (for example, Wikidata), OpenRefine attempts to match each artist name to an authoritative entity. If successful, it replaces the name in that column with a corresponding URI, providing a direct link to the external dataset. This step is crucial for producing data that is *linked* rather than merely enumerated, paving the way for more meaningful connections and queries within the knowledge graph.

6.2.3 Exporting to RDF

Once the data has been cleaned and entities resolved, the next challenge is to actually generate RDF from the refined table. For this, an OpenRefine extension named `RDF Refine` (previously developed by the Insight Centre in Galway and now maintained by the open-source community) offers a user-friendly interface to define how table columns map to RDF triples.

The extension uses a concept called *RDF skeletons* to specify the structure of the resulting triples. Each row in the table can be mapped to a resource in the RDF graph, and columns become predicates and objects according to the shape you define. As part of this skeleton, you can also integrate any external vocabulary by referencing namespaces or IRIs. For instance, a "Movie" could be linked to a class `mv:Movie`, and attributes like `mv:hasName` or `mv:hasReleaseDate` might map to columns in the table.

When the skeleton is fully specified, OpenRefine can export the table to standard RDF formats such as Turtle or RDF/XML. In a typical example:

```
<http://example-instance.org/The%20Shawshank%20Redemption> a mv:Movie;
   mv:hasName "The Shawshank Redemption";
   mv:hasReleaseDate "1994-01-01T00:00Z";
   mv:hasGenre "Drama";
   mv:hasMovieDirector <http://example-instance.org/Frank%20Darabont> .
```

This snippet shows how each movie row becomes an instance of `mv:Movie`, with properties corresponding to data columns and a URI-based identifier. If an external reconciliation step was used, these URIs might instead link to resources already existing in larger knowledge graphs such as Wikidata or DBpedia.

6.2.4 Summary and Further Pointers

Using OpenRefine for tabular data to RDF conversion thus entails four main phases: importing and cleaning the table, performing bulk transformations (including date conversions or text splitting), reconciling entities with an external service, and defining an RDF skeleton to guide the final export. The resulting dataset can then be ingested into a triple store or combined with other RDF data to form a more complete knowledge graph.

For those looking to try out this approach, the official OpenRefine website offers installers and documentation, while repositories for the RDF Refine extension provide instructions on enabling RDF export features. Sample projects, such as the one linked in many OpenRefine tutorials, showcase a straightforward path from messy CSV data to a cleaner, well-structured RDF representation.

6.3 Relational Data to RDF

A considerable amount of structured data is stored in relational databases. Converting this information into RDF is a key step in creating knowledge graphs that interoperate with other Linked Data. The W3C's RDB2RDF recommendation outlines two main approaches for achieving this: the *Direct Mapping* and the more flexible *R2RML* (RDB to RDF Mapping Language). While Direct Mapping automatically exposes a relational schema in RDF, it typically offers limited control over the resulting vocabulary and structure. In contrast, R2RML empowers data engineers to fully customize how they wish to represent database rows, columns, and relationships in an RDF graph.

6.3.1 Direct Mapping Overview

Direct Mapping provides a baseline procedure for automatically generating triples from relational tables without requiring extensive configuration. Every table is mapped to a class in RDF, each row becomes a resource (with a generated URI), and columns are translated into predicates. This approach can be useful for quickly publishing small databases or for experimentation, but it lacks explicit control over how to define the URIs, classes, or properties used in the final RDF representation. Consequently, the resulting graph may not use well-known vocabularies or only partially integrate with existing Linked Data.

6.3.2 R2RML: The RDB to RDF Mapping Language

R2RML offers the flexibility needed to create high-quality knowledge graphs. It is specified in RDF itself, meaning that one writes "mapping documents" describing how each table or SQL query, each row, and each column should be reflected in RDF. At a high level, an R2RML document consists of:

- `rr:logicalTable`: which table or query is being mapped,
- `rr:subjectMap`: instructions to generate the subject URI for each row,
- `rr:predicateObjectMap`: definitions of predicates and corresponding objects to produce the desired triples.

Instead of relying on generated names, developers can embed domain-specific vocabularies. For instance, a row in the "Person" table might be represented as an instance of `foaf:Person`, with properties such as `foaf:name` mapped from the `NAME` column. Within this framework, it becomes straightforward to:

1. Construct URIs from database identifiers, ensuring consistency and uniqueness.
2. Filter or transform data by using SQL queries instead of raw tables.
3. Reuse established ontologies and classes, thus integrating seamlessly with other Linked Datasets.
4. Interlink data by constructing URIs referencing external resources.

Below is a simplified example showing how a table named `Person` can be mapped into RDF resources of type `foaf:Person`:

```
@prefix rr: <http://www.w3.org/ns/r2rml#> .
@prefix foaf: <http://xmlns.com/foaf/0.1/> .

<TriplesMap1>
    a rr:TriplesMap ;
    rr:logicalTable [ rr:tableName "Person" ] ;
    rr:subjectMap [
        rr:template "http://www.ex.com/Person/{ID}" ;
        rr:class foaf:Person
    ] ;
    rr:predicateObjectMap [
        rr:predicate foaf:name ;
        rr:objectMap [ rr:column "NAME" ]
    ] .
```

In this snippet, each row in the `Person` table is turned into a `foaf:Person` whose URI is generated by replacing `{ID}` in the template with the value of the `ID` column. The `NAME` column is used as the object for the `foaf:name` predicate. Optionally, one can add further `rr:predicateObjectMap` sections for additional columns (such as `birthdate`) or even embed more intricate logic to join multiple tables.

6.3.3 Advanced Configuration

For more complex use cases, R2RML supports:

- **SQL Views and Filters:** Instead of mapping entire tables, one can define sub-queries that filter or join. This ensures only the relevant data appear as triples.
- **Join Conditions:** Inter-table relationships can be expressed by specifying how a foreign key column in one table links to a primary key in another, resulting in proper RDF links between resources.
- **Term Maps:** Columns can become IRIs, blank nodes, or literals. This is especially powerful when certain textual values need to be interpreted as IRIs referencing external entities.

- **Data Type Casting:** Numeric or date columns can be cast to matching XSD data types, preserving semantic precision in the resulting RDF.

6.4 Structured Data to RDF

While relational databases are a common source for RDF conversion via R2RML, many real-world data sources are more varied: JSON documents, XML feeds, CSV files with irregular structures, and so on. The RDF Mapping Language (RML) was conceived as a superset of R2RML in order to deal with these heterogeneous formats in a uniform way. Its aim is to preserve the essential mapping constructs from R2RML—such as logical tables, subject maps, and predicate–object maps—while adding extensions to handle non-tabular data and different ways of referencing values within those data sources.

6.4.1 RML Fundamentals and Motivation

RML extends the R2RML concept of a *logical table* (i.e., which part of the data one is mapping) by introducing the notion of *logical sources*. Instead of only referring to a table name or SQL query, an RML logical source can specify any input format and define how iteration over that data should occur. For example, JSON files often require a JSONPath expression to locate items, while XML might use XPath, and CSV might use a dedicated CSV-based query formulation. This generalization allows developers to maintain a consistent mapping approach across varied data formats.

The high-level structure of an RML mapping remains much the same as in R2RML:

- A `TriplesMap` block designates how certain portions of the input are transformed into RDF triples.
- A `rml:logicalSource` clause pinpoints the source and iteration method.
- A `rr:subjectMap` describes how to produce the subject URIs (or blank nodes) for each discovered record.
- One or more `rr:predicateObjectMap` sections define the RDF predicates and objects derived from fields in the source data.

However, the references in an RML mapping might point to JSON keys, XML elements, or CSV columns, depending on the `rml:referenceFormulation` in use. This mechanism gives a single specification language for data scattered among diverse file formats and structures.

6.4.2 RML in Practice

As a concrete illustration, one could have a JSON file containing a list of people. An RML logical source might specify `rml:source "people.json"` and an iterator of `rml:iterator "$.persons[*]"`, denoting that each entry in the `persons` array represents a record to be processed. If the JSON items have fields like `firstname` and `surname`, the RML mapping can instruct the engine to construct a subject URI (e.g., `http://ex.com/Person/{firstname}_{surname}`) and assign `foaf:Person` as the class, while also generating a `foaf:name` triple based on these fields.

Much like R2RML, RML supports the notion of joins: one can define how a child reference in one JSON structure links to a parent reference in another, thus forming relationships among different

parts of the data. This allows multiple `TriplesMap` blocks to cooperate, effectively bridging entities that appear in separate sections of the source or in separate files.

While RML offers broad flexibility, it may involve writing fairly verbose Turtle mappings. Additionally, different RML engines may handle certain aspects—such as advanced custom functions—differently. To mitigate these issues, developers can resort to frameworks like `carml` (for Java) or other community-maintained RML implementations, which parse RML into transformations that can run at scale. When advanced data manipulation is needed, a common best practice is to pre-process data externally before feeding it into an RML mapping, thereby reducing complexity at the mapping layer.

6.4.3 YARRRML: A More Accessible Syntax

For those who find Turtle-based RML definitions too cumbersome, a YAML-based syntax called **YARRRML** (*Yet Another RDF Refinement and Reasoning Mapping Language*) has emerged. YARRRML scripts express the same core mapping instructions as RML but in a more lightweight, human-readable format. Developers can translate YARRRML documents into valid RML automatically and then execute them with standard RML engines.

An example YARRRML snippet might define a `person` mapping, referencing a JSON source and specifying how to build the subject URI from a "firstname" property. Internally, this compiles to RML containing the appropriate `TriplesMap`, `subjectMap`, and `predicateObjectMap` directives. Thus, YARRRML can enhance productivity, especially for iterative mapping tasks or rapid prototyping.

6.4.4 Points to Consider and Further Resources

Although RML and its derivatives greatly simplify the ingestion of heterogeneous data into RDF, a few practical notes arise:

- Different engines may vary in their support for custom functions or certain path expressions, so it is important to check compatibility.
- Tools such as online JSONPath or XPath editors can help validate that the desired data is being retrieved at each iteration before finalizing an RML mapping.
- GUIs like the RML Editor (`https://rml.io/tools/rmleditor/`) or approaches involving YARRRML can reduce the overhead of crafting raw RML mappings in Turtle.
- If the data is fundamentally tabular, approaches like OpenRefine plus its RDF extension may be more efficient in cleansing and transforming the dataset before final conversion to RDF.

When properly configured, RML becomes a powerful method to unify CSV, JSON, XML, and other structures into a coherent RDF graph. By imposing a consistent subject–predicate–object framework across heterogeneous data, organizations can more readily interlink resources, integrate them with existing Linked Data, and generate knowledge graphs that reflect the complexity of their real-world contexts.

6.5 Text to RDF

One of the most challenging aspects of knowledge graph creation is extracting structured information from free-text resources. While tabular and relational data typically follow well-defined schemas, text is unstructured by nature. Tools and frameworks for *semantic annotation* attempt to bridge this

gap by detecting and linking concepts, entities, or relationships within text to RDF vocabularies and external Linked Data resources. This process can significantly enrich a knowledge graph, allowing it to capture both explicit and implicit information about entities mentioned in documents, articles, and other textual sources.

6.5.1 Semantic Annotation: Formal Modeling and Motivation

Semantic annotation refers to attaching explicit, structured information (annotations) to segments of text. In an RDF context, each annotation can be viewed as a statement that connects a piece of text (*the annotated data*) to a resource or concept (*the annotating data*) via a specific relation. Formally, an annotation A can be defined as a tuple (a_s, a_p, a_o, a_c), where:

- a_s is the subject being annotated (the text or document segment),
- a_p is the predicate expressing the nature of the annotation (e.g., `dbo:author` or `rdfs:comment`),
- a_o is the object (the concept or additional data that annotates a_s),
- a_c is contextual information, such as the provenance or scope of the annotation.

By representing these annotations in RDF, documents can be linked to external entities, making the information discoverable and machine-processable. For instance, a reference to "Stanley Kubrick" in a paragraph can be associated with the corresponding `dbr:Stanley_Kubrick` resource in DBpedia, thus connecting the text to a broad array of related data.

6.5.2 Annotation Ontologies and Standards

To promote interoperability and reusability of annotations, standard ontologies have emerged. One of the most prominent is the *Open Annotation Ontology*, now W3C's *Web Annotation Data Model*, which defines best practices for creating and sharing annotations across multiple platforms and domains. In this model:

- An `oa:Annotation` entity ties together the *Target* (the text segment or media being annotated) and the *Body* (the additional information or resource describing or contextualizing the target).
- A `SpecificResource` or a `Selector` can be used to pinpoint exact positions within a text, e.g., character offsets for a mention or a region in an image.

Using these constructs, tools can highlight a mention of "Neil Armstrong" in a sentence and map that mention to the DBpedia resource `dbr:Neil_Armstrong`, along with any other relevant metadata (date created, annotator, confidence scores, etc.).

6.5.3 Annotation Tools and Services

A variety of tools exist to perform semantic annotation, each bringing its own approach to Natural Language Processing (NLP), named entity recognition, and entity linking:

DBpedia Spotlight. This open-source tool detects mentions in text and links them to corresponding DBpedia URIs. It supports multiple languages and can be accessed via a web service, Java/Scala APIs, or plugins for languages like Python or PHP. When used in a pipeline, DBpedia Spotlight transforms unstructured text into a semantically richer form by exposing entities and properties that map back to the Linked Open Data (LOD) cloud.

PermID (OpenCalais). Offered by Refinitiv (formerly Thomson Reuters), the PermID service—descendan of OpenCalais—provides powerful text analytics for identifying entities, relationships, and events. Though it is a commercial product, it integrates well with existing knowledge graphs via stable PermIDs, ensuring consistent entity URIs across different data sources.

GATE (General Architecture for Text Engineering). An established open-source framework for text analysis, GATE provides a configurable environment for building *bespoke* annotation pipelines. Developers can combine pre-built NLP components—tokenizers, part-of-speech taggers, named entity recognizers—with domain-specific modules to tailor extraction for specialized tasks. This is especially helpful when the text is highly domain-specific (medical, legal, etc.) and general-purpose annotators produce suboptimal results.

6.5.4 From Document to Knowledge Graph

Semantic annotation is most beneficial when the resulting annotations are expressed in RDF and integrated into the broader knowledge graph. A typical workflow might include:

1. **Text Preprocessing.** Cleaning the text, splitting it into sentences or sections, and normalizing characters.
2. **Annotation.** Passing each document to a chosen tool (e.g., DBpedia Spotlight or GATE) that detects entity mentions, relationships, or other relevant features.
3. **Triple Generation.** Converting discovered annotations into RDF triples, referencing vocabularies like `dbo:`, `foaf:`, `schema:`, or application-specific predicates. The text segments themselves may become subjects (or remain as literal strings) in the final RDF model.
4. **Storage and Query.** Persisting the generated triples in a triplestore or knowledge graph. Queries can then combine structured data, such as *which entity occurs in which document segment*, or advanced questions that blend text-derived knowledge with relational or hierarchical information from other parts of the graph.

By adopting standard models and robust annotation pipelines, text can be transformed from inert strings into linked resources. This provides deeper insights, fosters content discovery, and facilitates data-driven analysis. In large organizations, such a process enables knowledge workers to locate all references to a particular entity across numerous documents, bridging the gap between unstructured text and structured data management.

6.6 RDF Storage

Storing RDF data efficiently is an important step in building knowledge graphs that scale to large or complex datasets. A core challenge lies in balancing the flexibility of the triple-based data model with performance concerns typically associated with high-volume query processing. Numerous storage strategies have emerged over the years, each making different trade-offs regarding indexing, data layout, and distribution. Broadly, we can divide these storage architectures into *centralized* and *distributed* systems, depending on whether they run on a single node or across a cluster.

6.6.1 Centralized vs. Distributed Systems

A *centralized* RDF store runs on a single node, managing all data and queries locally. These systems tend to be simpler to configure and can be highly optimized for small- to medium-scale datasets. In contrast, *distributed* systems partition data across multiple nodes. This approach accommodates very large datasets and heavy query loads, at the expense of increased complexity in data partitioning and query coordination. As data volume grows and query workloads intensify, distributed solutions may become necessary to maintain acceptable performance.

6.6.2 Common RDF Storage Approaches

Although designs vary, several canonical approaches dominate the landscape of RDF storage. Each approach offers distinct strengths depending on the nature of the data and the query patterns expected:

Statement Tables. Often considered the most direct strategy, *statement tables* store each triple as a row in a universal table with columns for subject, predicate, and object. This linearized structure requires minimal preprocessing and naturally supports the triple model. However, queries involving multiple predicates often necessitate expensive self-joins, reducing performance when the dataset or query complexity grows. Systems such as Jena SDB, 3Store, 4Store, and Virtuoso can store data in statement-table-like formats, sometimes with additional indexing to mitigate join costs.

Property Tables. The *property table* approach attempts to reduce self-joins by placing commonly co-occurring predicates (properties) into a single table with multiple columns. Each row in this table corresponds to a subject, with columns for each property. Clustering these related properties can reduce the number of joins needed for queries that frequently access them together. Systems like DB2RDF and Jena2 SDB adopt property tables in certain configurations, although deciding which properties to cluster is itself a nontrivial design issue.

Index Permutations. An alternative strategy is to build multiple indexes of the triple data in different permutations of subject, predicate, and object. Systems such as *Hexastore* and *RDF-3X* index all six permutations of the triple components (SPO, SOP, PSO, POS, OSP, OPS). By providing every possible ordering as an index, queries can look up triples efficiently, often leading to very fast merge joins. The trade-off lies in increased storage overhead from maintaining so many indexes, as well as the update cost when data changes.

Vertical Partitioning. A *vertical partitioning* approach creates one table per property in the dataset. Each table contains two columns: subject and object. Multi-valued properties lead to additional rows within the same property table, and each table is usually indexed by subject. Because queries that filter by property can scan only the relevant table, the approach often leads to faster retrieval for property-specific queries. However, queries involving many properties simultaneously may require multiple lookups, potentially complicating join logic. The *SW-Store* system is often cited as a prominent example of vertical partitioning.

6.6.3 Selecting the Right Approach

Choosing an appropriate RDF storage strategy hinges on the expected usage patterns, dataset size, and operational constraints:

- **Frequent multi-property queries:** Consider property tables or index permutation systems. By bringing together related data or offering multiple access paths, they reduce the number of expensive joins.
- **Extremely large or distributed datasets:** Evaluate distributed systems that partition data and parallelize queries. Vertical partitioning or statement tables distributed across nodes can also help, although the orchestration layer becomes more involved.
- **Simplicity and generality:** A straightforward statement-table design can be implemented quickly and is flexible enough to handle arbitrary RDF, making it suitable for prototyping or modest dataset sizes.

Overall, there is no one-size-fits-all solution for RDF storage. Instead, engineers typically test multiple approaches, balancing storage overhead and query performance while considering ease of implementation. Understanding these core techniques provides a solid foundation for deploying an RDF backend that can support knowledge graph creation and querying at scale.

7 Extras

The evolution of knowledge graphs—spanning research endeavors and widespread industry adoption—demonstrates their power to integrate, manage, and extract value from vast and heterogeneous datasets. Over the years, we have witnessed significant breakthroughs, from the first conceptualizations of the Semantic Web to today's AI-driven initiatives that fuse symbolic reasoning with deep learning. Below is a concise look at emerging themes and applications that illustrate how knowledge graphs continue to transform data management and analytics across various domains.

7.0.1 Historical Context and Transition to Knowledge Graphs

The foundational ideas of semantic systems and knowledge representation date back to Tim Berners-Lee's vision of the Semantic Web, famously articulated in the 2001 *Scientific American* article on the future of web data. The ultimate "killer app" envisioned was an ecosystem of intelligent agents capable of automatically scheduling appointments, negotiating services, and making decisions on behalf of users, all by leveraging standardized data representations. While this level of agent autonomy remains a long-term goal, the building blocks—structured data, ontologies, and Linked Data principles—have materialized in a more immediate sense through knowledge graphs that power modern search engines, recommender systems, and advanced analytics.

7.0.2 Industry Impact and Linked Data Growth

Industry adoption of knowledge graphs has accelerated in the past decade. Large-scale enterprises (e.g., in the web search, e-commerce, and social media sectors) leverage graphs to store and query factual data about billions of entities, vastly improving the quality and intelligibility of their products. Meanwhile, open knowledge graphs such as DBpedia, Wikidata, Bio2RDF, and the Linked Open Data cloud have continued to expand, providing a wealth of structured data that benefits various academic and commercial applications. This openness fosters collaborative cross-domain analysis, enabling novel insights in areas from biomedical research to climate monitoring.

7.0.3 Neurosymbolic AI

A notable trend is the rise of *neurosymbolic AI*, which aims to unify neural networks (pure machine learning) with symbolic knowledge reasoning (pure logic). By combining robust pattern recognition with the interpretability and structure of symbolic reasoning, we can craft AI systems that:

- Use knowledge graph edges and types to guide or constrain neural models.
- Provide traceable, explainable outcomes, helping domain experts scrutinize how decisions are reached.
- Handle incomplete or uncertain data in a consistent framework, often relying on partial completeness assumptions or uncertain reasoning.

The knowledge graph thus acts as the backbone, offering an interpretable semantic layer for data-driven algorithms.

7.0.4 Data Fabrics and Semantic Data Lakes

Traditional data warehousing models are often being superseded or supplemented by *data lakes*—unified repositories of raw data from diverse sources. However, without semantic annotation or modeling, these lakes quickly become "data swamps." *Data fabrics* and *semantic data lakes* introduce knowledge graphs as a unifying schema layer, ensuring consistent interpretations of data elements across organizational silos. By employing standard ontologies and cross-dataset links, data fabrics can power advanced analytics, machine learning, and real-time data integration. This approach is crucial in contexts like scientific data management (e.g., integrating genome sequences with soil metadata and satellite imagery) or large-scale enterprise data catalogs.

7.0.5 Provenance and Explainability

As systems become more data-driven, there is heightened demand for *explainability* and *provenance*. Users increasingly want to know:

- *Where* a piece of information originated.
- *How* a query result was derived (which triples or inference rules contributed to the final answer).
- *Why* certain data was included or excluded in an analysis.

Research in SPARQL *how-provenance* addresses these questions by assigning identifiers to triples and rewriting queries to track contributions to each result. In parallel, frameworks like PROV-O define ontologies for describing the provenance of data transformations. Together, these solutions bolster trust and interpretability in knowledge graphs used for mission-critical tasks.

7.0.6 Use Cases and Future Directions

Healthcare and Bioinformatics. From electronic health records to genomic data, knowledge graphs can unify patient information, medication histories, and disease ontologies. Combined with explainable AI techniques, clinicians can better trace diagnosis steps or medication recommendations.

Sustainability and Circular Economy. Governments, organizations, and researchers employ knowledge graphs for environmental data integration—ranging from complex climate models to local land-use data. Semantic annotation of policy documents and green finance data fosters transparency and shapes evidence-based decision-making.

Media, Entertainment, and Cultural Heritage. By semantically annotating media assets and historical archives, cultural institutions can create rich interactive experiences, enabling new forms of curation and cross-collection linkage.

Transportation and Logistics. Large-scale logistics operations rely on integrated data about routes, cargo, and weather conditions. Knowledge graphs, combined with federated queries, can unify these streams and support real-time decision-making.

Manufacturing and Industry 4.0. Smart factories adopt semantic layers to model machine components, processes, and IoT sensor data. The resulting knowledge graphs improve process optimization, fault detection, and supply chain coordination.

Looking forward, knowledge graphs will continue to expand their horizons by blending advanced reasoning, neural models, and streaming data sources. These developments will call for scalable storage, query optimization, and robust data governance. It is exactly in this interplay of technology, data management, and semantics that knowledge graphs shine—turning raw data into contextualized, intelligent, and actionable knowledge.