

Linked Data & Semantic Web (2021-2A)

Ontology Matching

Shenghui Wang

22 March 2022

Goals of today's lecture

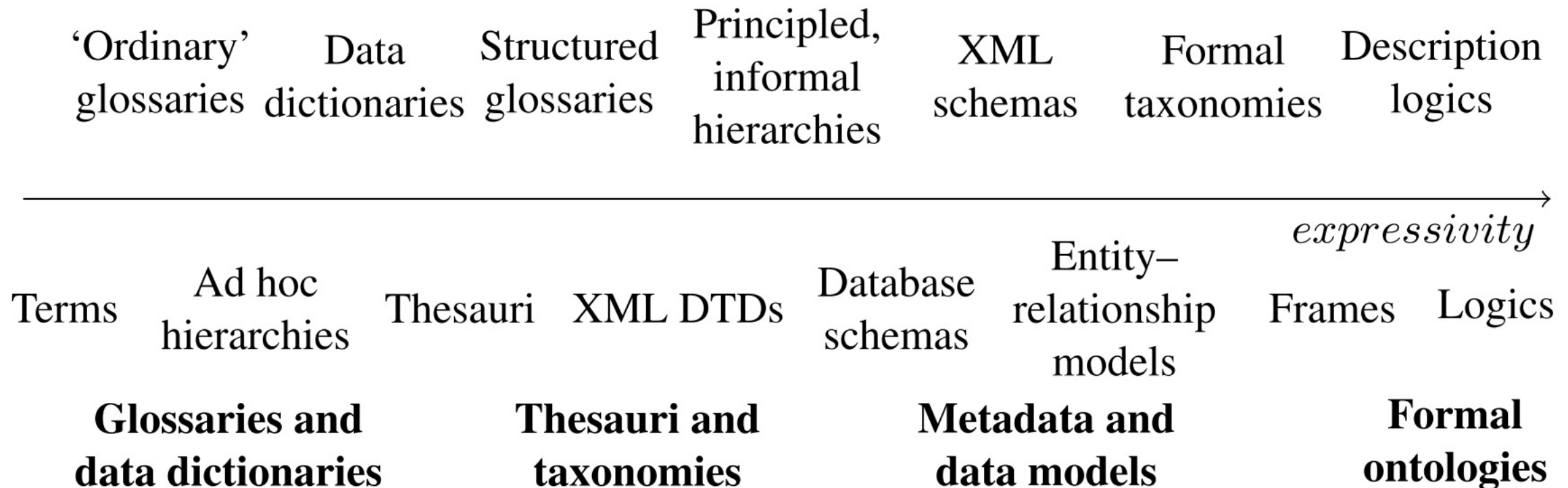
- Introduce what ontology matching is and why it is important
- Discuss practical and methodological issues
- Describe different techniques for ontology matching
- Evaluate the quality of ontology matching

Introduction

What is an ontology?

- An ontology typically provides a **vocabulary** describing a domain of interest and a **specification of the meaning** of terms in that vocabulary
- Depending on the precision of this specification, the notion of ontology encompasses several data and conceptual models, including, sets of terms, classifications, thesauri, database schemas, or fully axiomatized theories.

Various forms of ontologies

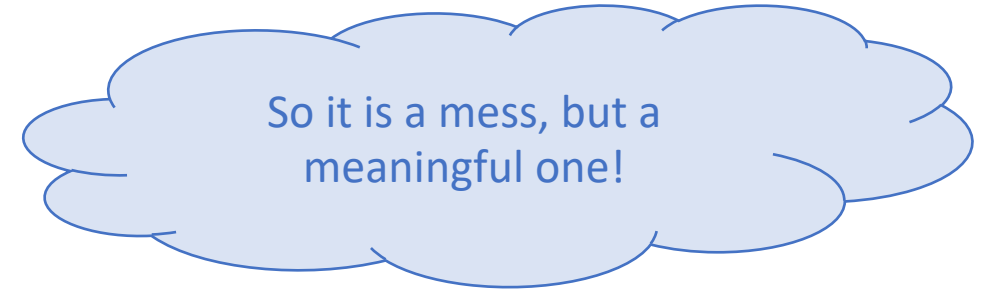
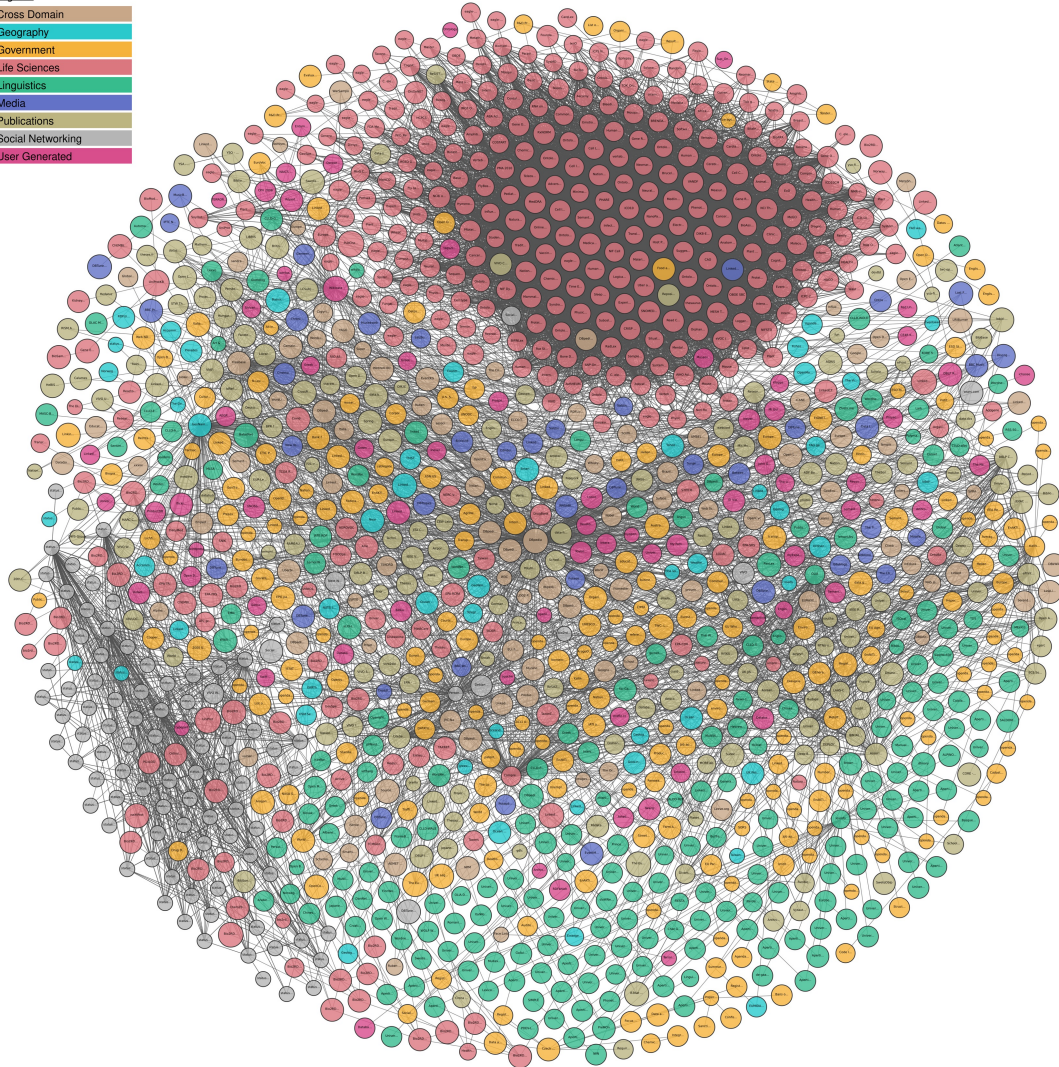


Ontologies are not Reality

- Ontologies are a context-dependent projection (model) of the Reality
- Different ontologies might model the same (similar) or highly related domains, but they might
 - Reflect different tasks and requirements of applications
 - Follow different conventions and restrictions

Linked Open Data cloud

Legend
Cross Domain
Geography
Government
Life Sciences
Linguistics
Media
Publications
Social Networking
User Generated



Legend

Cross Domain

Geography

Government

Life Sciences

Linguistics

Media

Publications

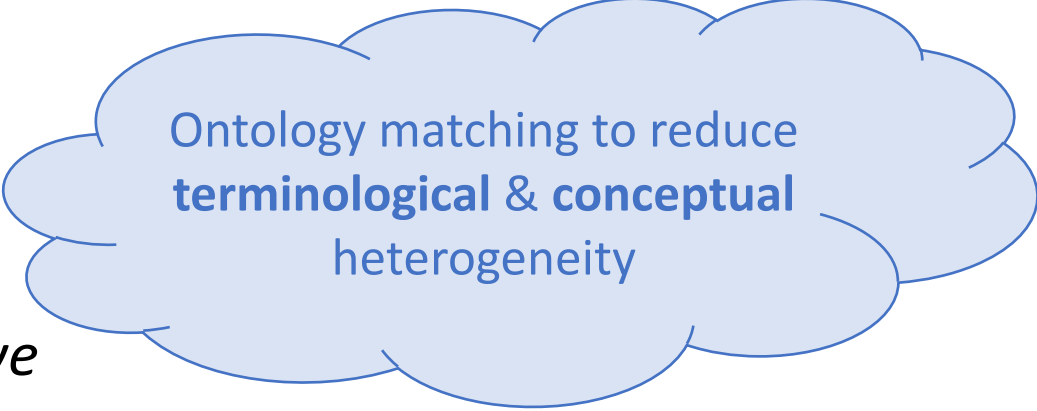
Social Networking

User Generated

<https://lod-cloud.net/>

The heterogeneity problem

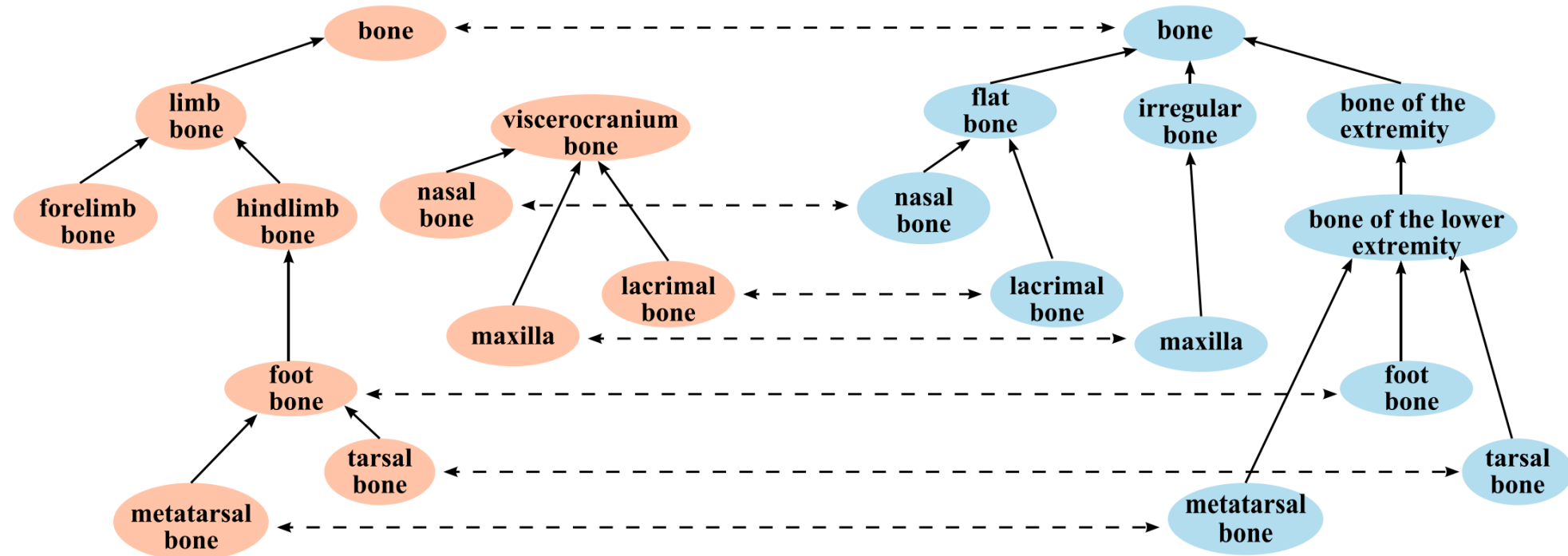
- **Syntactic** heterogeneity
 - Using different ontology languages (e.g. XML, OWL)
- **Terminological** heterogeneity
 - Different terms refer to the same concept
 - Same term describes different concepts
- **Conceptual (Semantic)** heterogeneity
 - Difference in *granularity, coverage, perspective*
- **Semiotic (Pragmatic)** heterogeneity
 - Different interpretations wrt different context



Ontology matching to reduce
terminological & conceptual
heterogeneity

What is ontology matching?

- Ontology matching, is the process of determining correspondences between concepts in ontologies.



Correspondence

- Given two ontologies o and o' , a **correspondence** between o and o' is defined as $\langle id, e, e', r, n \rangle$,

where

- id is a unique identifier of the correspondence
- e and e' are entities of o and o' respectively, e.g., classes, instances
- r is a relation, e.g., equivalence($=$), more general (\supseteq), more specific (\sqsubseteq), disjointness (\perp), etc.
- n is a confidence measure (typically in a range of $[0,1]$) for the correspondence between e and e' .

Correspondence relations

- OWL
 - owl:equivalentClass, owl:equivalentProperty
 - owl:sameAs, owl:differentFrom, owl:AllDifferent
- SKOS
 - skos:exactMatch, skos:closeMatch
 - skos:broadMatch, skos:narrowMatch
 - skos:relatedMatch

Alignment

- Given two ontologies o and o' , an **alignment** between o and o' :
 - is a set of correspondences on o and o'
 - with some additional metadata
 - multiplicity: 1:1, 1:m, m:n
 - method
 - date
 - creator
 - ...

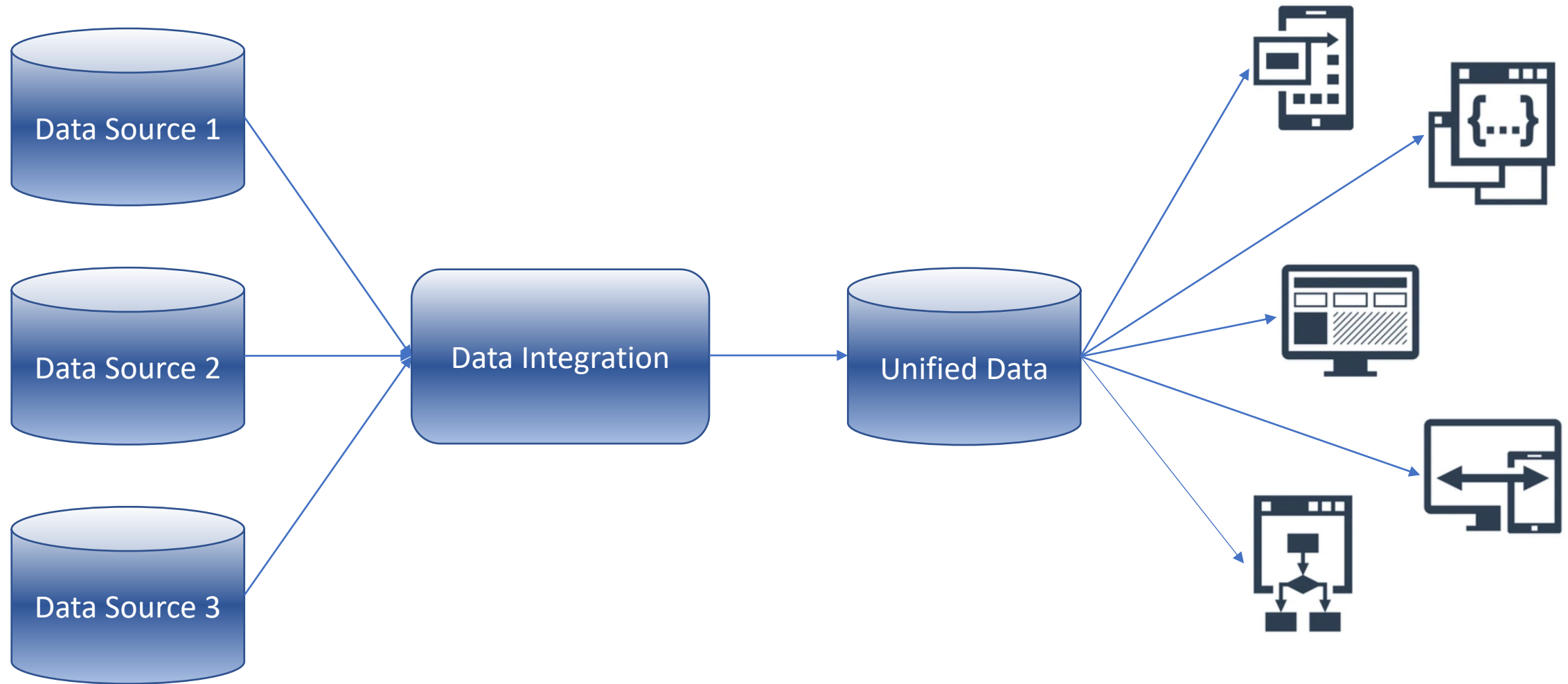
Terminology

- **Matching** is the process of finding relationships or correspondences between entities of different ontologies.
- **Alignment** is a set of correspondences between two or more (in case of multiple matching) ontologies. The alignment is the output of the matching process.
- **Correspondence** is the relation supposed to hold according to a particular matching algorithm or individual, between entities of different ontologies.
- **Mapping** is the oriented, or directed, version of an alignment.

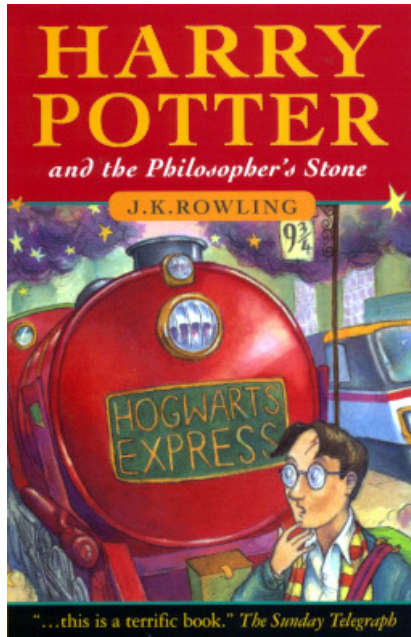
Ontology matching applications

Application	instances	run time	automatic	correct	complete	operation
Ontology evolution	✓			✓	✓	transformation
Schema integration	✓			✓	✓	merging
Catalog integration	✓			✓	✓	data translation
Data integration	✓			✓	✓	query answering
Linked data	✓			✓		data interlinking
P2P information sharing		✓				query answering
Web service composition		✓	✓	✓		data mediation
Multi agent communication		✓	✓	✓	✓	data translation
Query answering	✓	✓				query reformulation

Data Integration



Let's look at an example



- **Title:** Harry Potter and the Philosopher's Stone
- **Author:** J. K. Rowling
- **Illustrator:** Thomas Taylor
- **Publication year:** 1997
- **Publisher:** Bloomsbury (UK)
- **ISBN:** 0-7475-3269-9

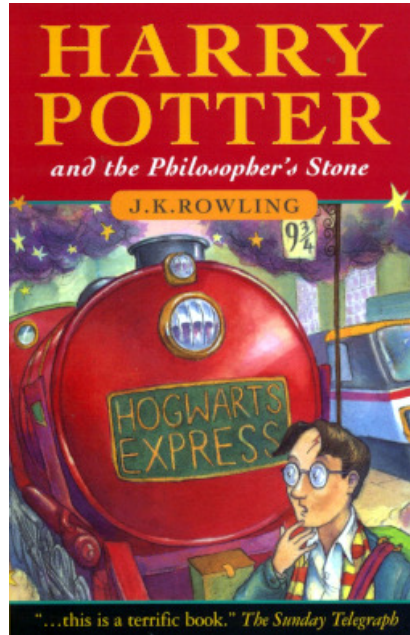


- **Title:** Harry Potter and the Philosopher's Stone
- **Author:** J. K. Rowling
- **Subjects:** Juvenile fiction, fantasy fiction
- **Dewey:** 823.914 <- English fiction, between 1945 and 1999
- **Publication details:** London : Bloomsbury, 1997 2004 printing.
- **ISBN:** 0747574472 (pbk)



- **Title:** Harry Potter and the sorcerer's stone
- **Uniform title:** Harry Potter and the philosopher's stone
- **Personal name:** Rowling, J. K., author
- **Published/Produced:** New York, NY : Scholastic Inc., [2018]
- **ISBN:** 9781338299144 (paperback), 133829914X (paperback)
- **LC Subjects:** Wizards—Fiction, Magic—Fiction, Schools-Fiction
- **Dewey class no.:** 823/.914 [Fic]
- **Summary:** Rescued from the outrageous neglect of his aunt and uncle, a young boy with a great destiny proves his worth while attending Hogwarts School for Witchcraft and Wizardry.

After data integration



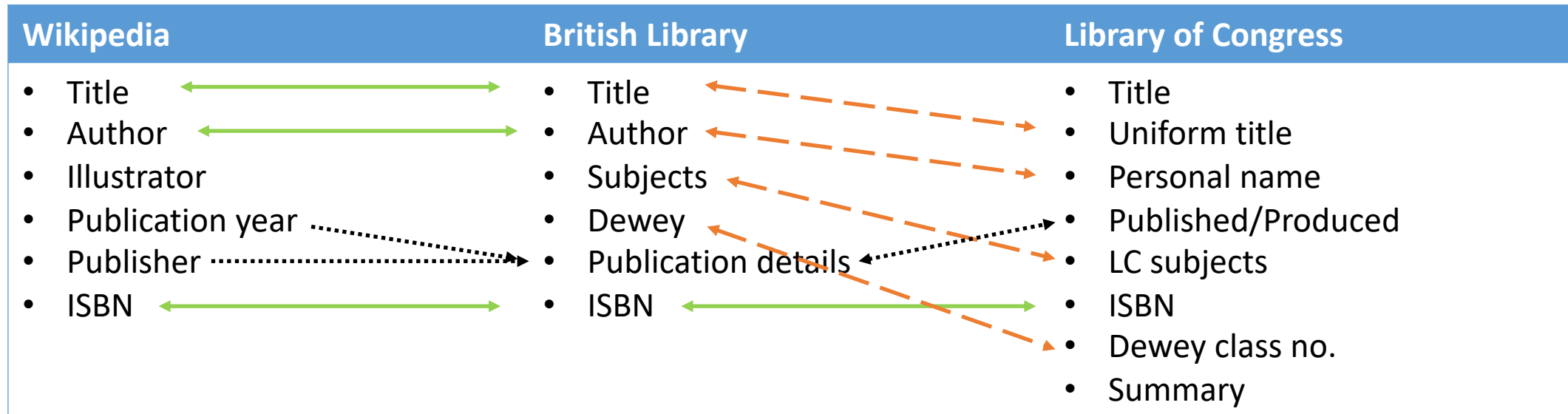
- **Title:** Harry Potter and the Philosopher's Stone
- **Other title:** Harry Potter and the sorcerer's stone
- **Author:** J. K. Rowling
- **Illustrator:** Thomas Taylor
- **Publication year:** 1997
- **Publisher:** Bloomsbury (UK)
- **ISBN:** 0-7475-3269-9, 0747574472 (pbk), 9781338299144 (paperback), 133829914X (paperback)
- **Subjects:** Juvenile fiction, fantasy fiction, Wizards—Fiction, Magic—Fiction, Schools-Fiction
- **Dewey:** 823.914
- **Summary:** Rescued from the outrageous neglect of his aunt and uncle, a young boy with a great destiny proves his worth while attending Hogwarts School for Witchcraft and Wizardry.

Data Integration

- **Schema matching** focuses on finding the correspondence among schema elements in two semantically correlated schemata
- **Schema mapping** describes how a source database schema relates to a target database schema
- **Record linkage** (also known as entity resolution and deduplication) identifies records that refer to the same logical entity
- **Data fusion** focuses on resolving conflicts and determining the true data values, leveraging information in heterogeneous data sources

Data integration challenges

- Attributes may have different names-> entity attributes need to be **mapped**



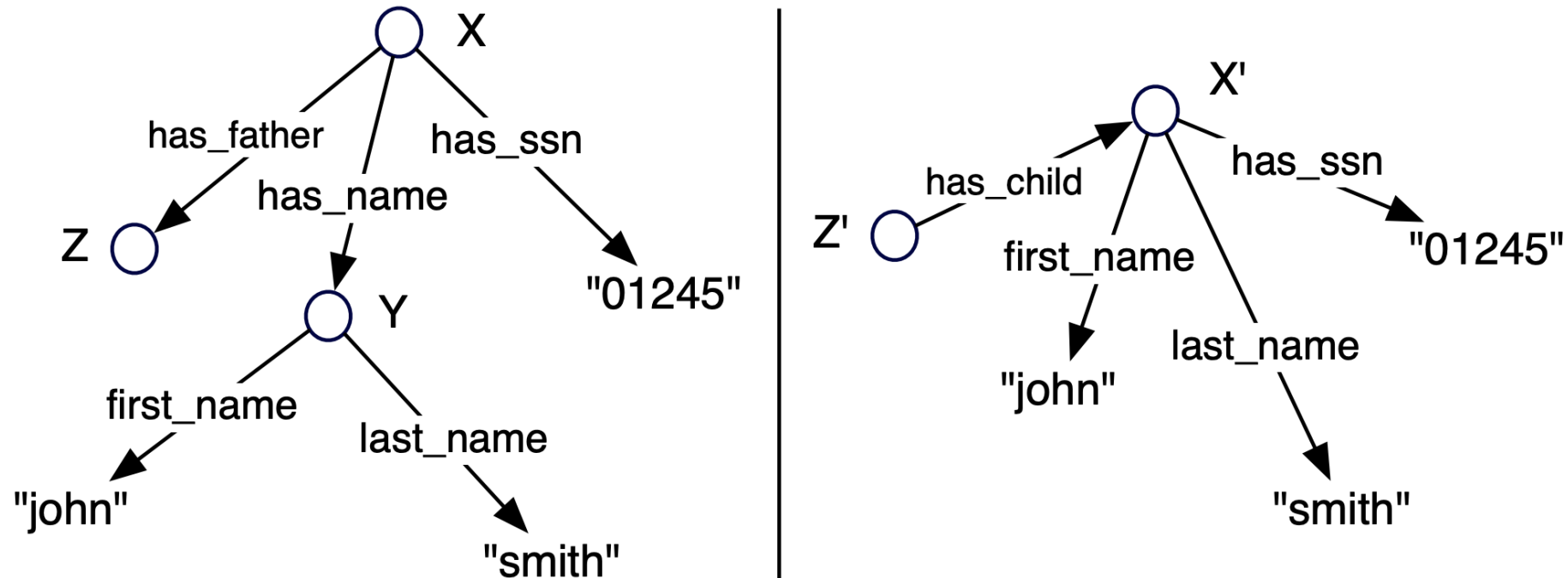
Data integration challenges

- Attribute values are not the same -> inconsistency needs to be resolved during **merging**

	Wikipedia	British Library	Library of Congress
Title	Harry Potter and the Philosopher's Stone	Harry Potter and the Philosopher's Stone	Harry Potter and the sorcerer's stone
ISBN	0-7475-3269-9	0747574472 (pbk)	9781338299144 (paperback), 133829914X (paperback)
Subject		Juvenile fiction, fantasy fiction	Wizards—Fiction, Magic—Fiction, Schools-Fiction
Dewey		823.914	823/.914 [Fic]
Publishing status	<ul style="list-style-type: none">• Publication year: 1997• Publisher: Bloomsbury (UK)	<ul style="list-style-type: none">• Publication details: London : Bloomsbury, 1997 2004 printing.	<ul style="list-style-type: none">• Published/Produced: New York, NY : Scholastic Inc., [2018]

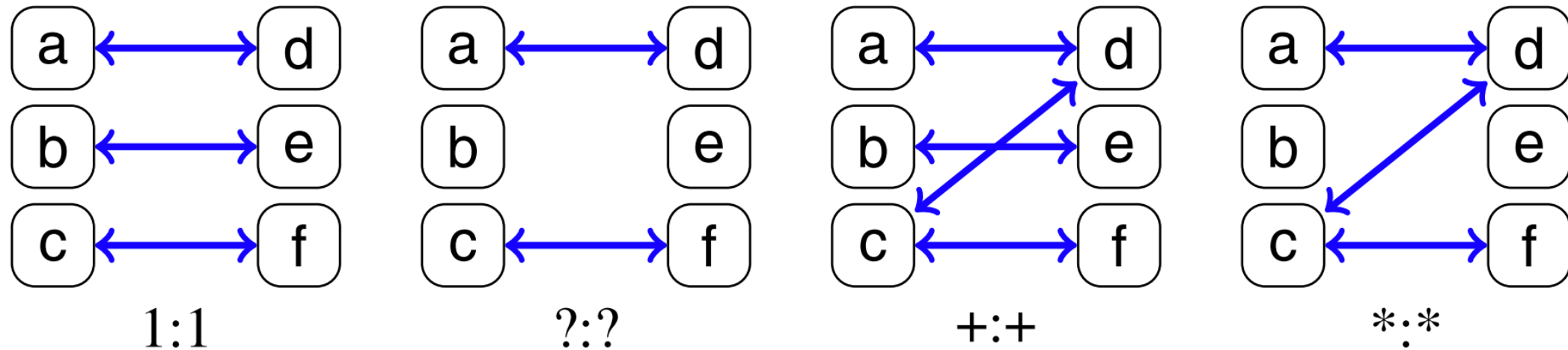
Data integration challenges

- Structural heterogeneity



Data integration challenges

- Multiplicity
 - 1:1, 1:n, m:1, or m:n?
 - This applies to both entities and attributes



Data integration challenges

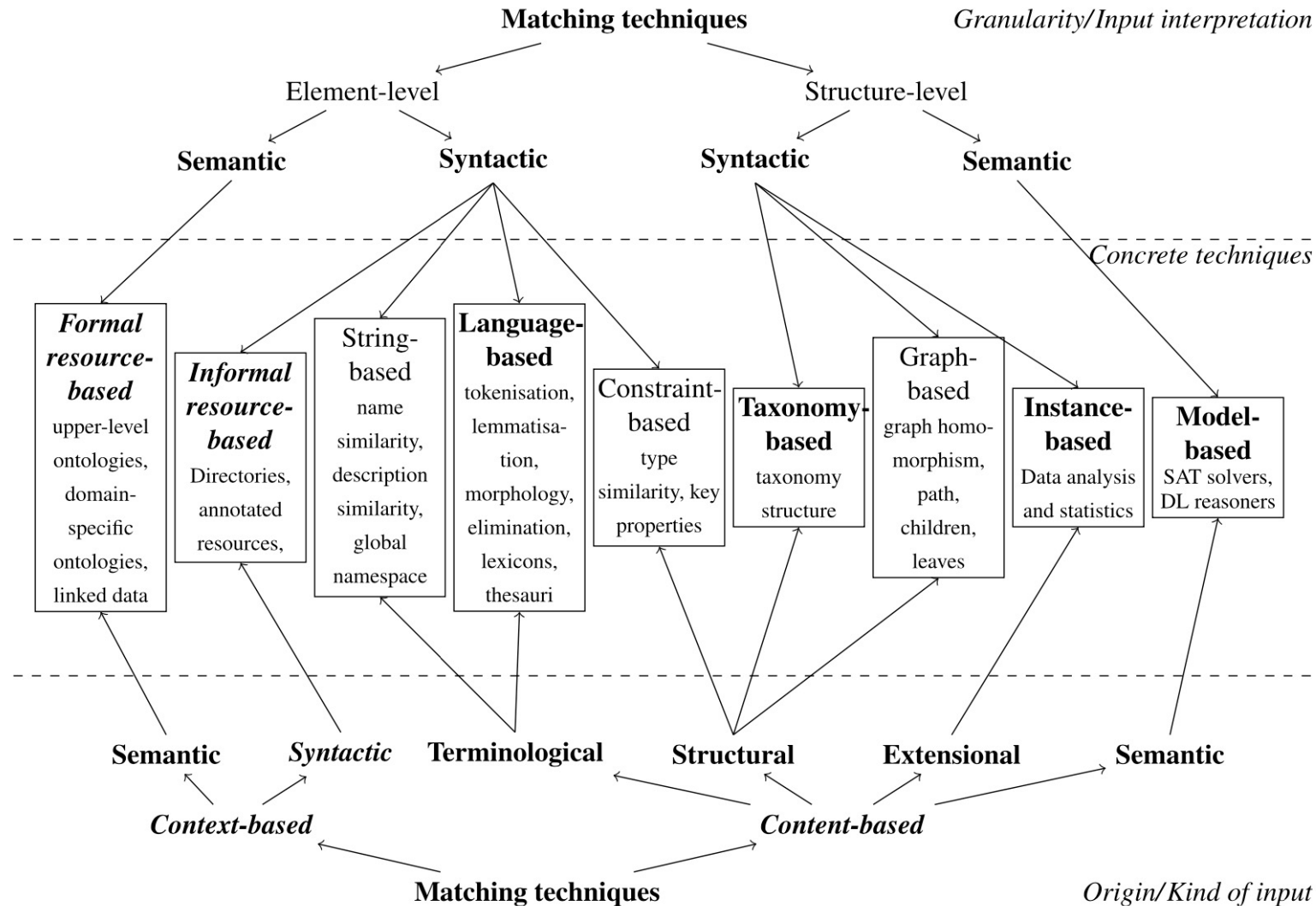
- Matching score and threshold
 - `<wiki:title> <bl:title>` 1.0
 - `<bl:Publication_details> <loc:Published_Produced>` 0.7
 - False positive vs false negative
- Data sets are too big -> Scalability issues
 - Library of Congress has 19M+ book records, while British Library has 25M+ and WorldCat 400M+!
 - Optimisations
 - Reduction of the number of comparisons
 - Reduction of the cost of each comparison

Schema and instance matching

Ontology matching

- A **schema** is a structure of **metadata** describing how data, i.e., **instances**, can be stored, accessed, and interpreted by users and applications.
- Schema matching
 - Whether two concepts (e.g., *book* vs *manuscript*) or two properties (e.g. *birthplace* vs *hometown*) are the same
- Instance matching
 - Whether different instances refer to the same real-world entity in a given domain (e.g., a person, a place, a movie, a book, etc.)

Classification of schema matching techniques



Categories of matching techniques

- **Element-level** techniques consider ontology entities or their instances in isolation from their relations with other entities or their instances
- **Structure-level** techniques consider the ontology entities or their instances to compare their relations with other entities or their instances.

Element-level techniques

- **String-based**: matching names or descriptions of entities
- **Linguistic-based**: use NLP, lexicons, or domain specific thesauri to match words based on linguistic relations (homonymy, synonymy, partonomy, etc) or exploiting morphological properties
- **Constrained-based**: take into account internal constraints applied to the definitions of entities, e.g. types, cardinality of properties, etc.
- **Resource-based**: use external upper-level or domain-specific ontologies to bridge classes to be matched.

Element-level techniques: string-based

- **Levenshtein distance** represents the number of insertions, deletions, and substitutions required to change one word to another.
 - For example, the Levenshtein distance between "kitten" and "sitting" is 3:
 - kitten → sitten (substitution of "s" for "k"),
 - sitten → sittin (substitution of "i" for "e"),
 - sittin → sitting (insertion of "g" at the end).
- **Damerau-Levenshtein distance** counts transpositions as a single edit
 - For example, `damerau_levenshtein_distance('fish', 'ifsh') == 1` while `levenshtein_distance('fish', 'ifsh') == 2`

Element-level techniques: string-based

- **Hamming distance** between two equal-length strings of symbols is the number of positions at which the corresponding symbols are different.
 - For example, the Hamming distance between "karoln" and "kerstn" is 3.
- **N-gram**
 - Takes as input two strings and calculate the number of the common n-grams between them, normalised by $\max(\text{length}(\text{string1}), \text{length}(\text{string2}))$
 - Trigrams for **matching** is **mat, atc, tch, chi, hin, ing**

Element-level techniques: linguistic-based

- Tokenization
 - Parses names into tokens by recognizing punctuation, cases
 - **string-based methods** -> [**string**, **based**, **methods**]
- Lemmatisation
 - Analyses morphologically tokens to find their basic forms
 - **methods** -> **method**
- Remove stop words
 - **a, he, them, by, from**

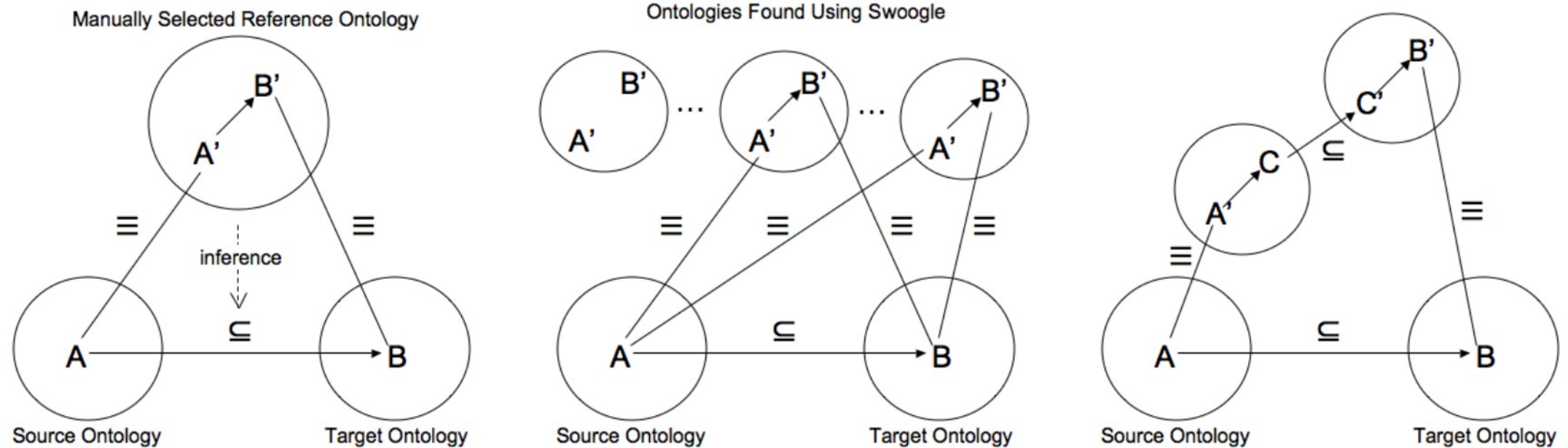
Element-level techniques: phonetic-based

- Phonetic encoding
 - The goal is for homophones to be encoded to the same representation so that they can be matched despite minor differences in spelling.
 - Soundex is a phonetic algorithm for indexing names by sound, as pronounced in English.
 - `soundex('Ashcraft') == soundex('Ashcroft') == 'A261'`
 - `Soundex('Rupert') == soundex('Robert') == 'R163'`

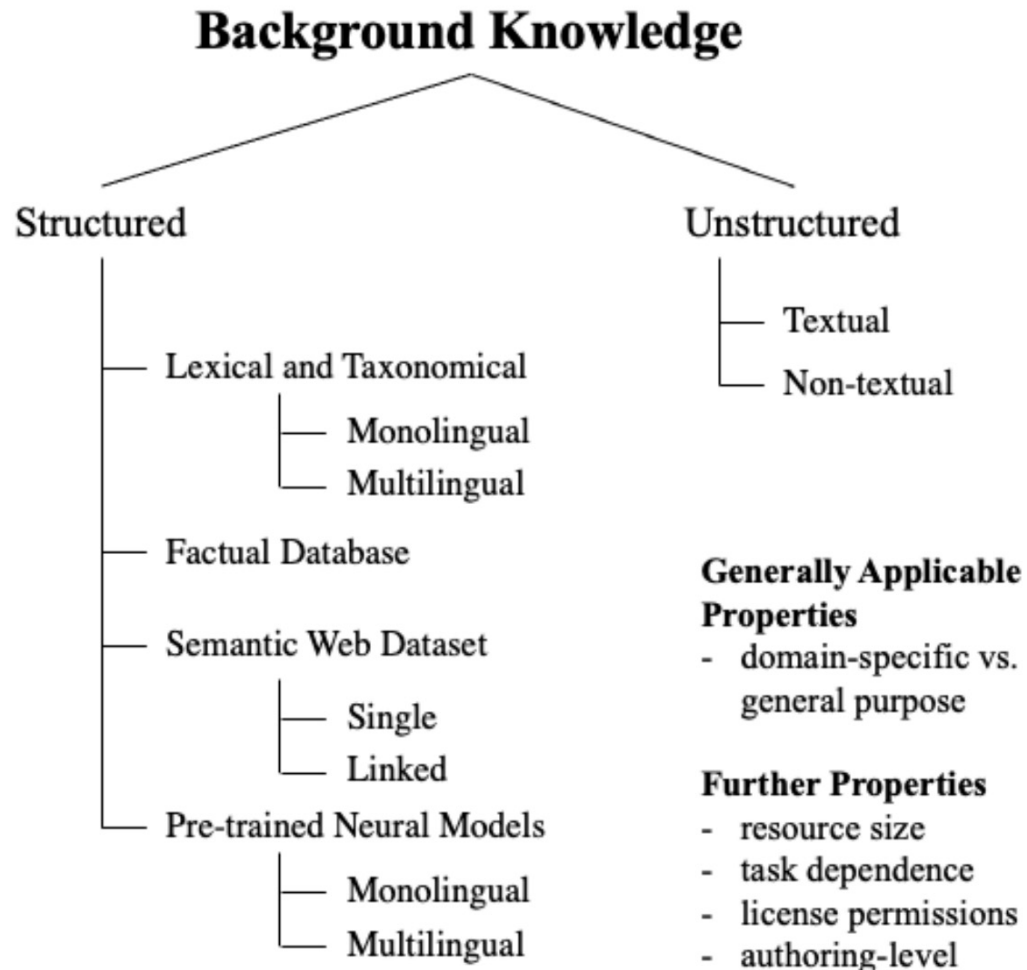
Element-level techniques: resource-based

- Sense-based: WordNet
 - $A \sqsubseteq B$ if A is a hyponym or meronym of B
 - $\text{apple} \sqsubseteq \text{fruit}$
 - $A \sqsupseteq B$ if A is a hypernym or holonym of B
 - $\text{animal} \sqsupseteq \text{cat}$
 - $A = B$ if A and B are synonyms
 - $\text{student} = \text{pupil}$
 - $A \perp B$ if A and B are antonyms or the siblings in the part of hierarchy
 - $\text{giant} \perp \text{dwarf}$

Element-level techniques: resource-based



Background knowledge-based matching



Most Used Background Knowledge Resources:

- WordNet
- Translation APIs
- Biomedical ontologies, e.g., UMLS, UBERON, BioPortal, MeSH

Structure-level techniques

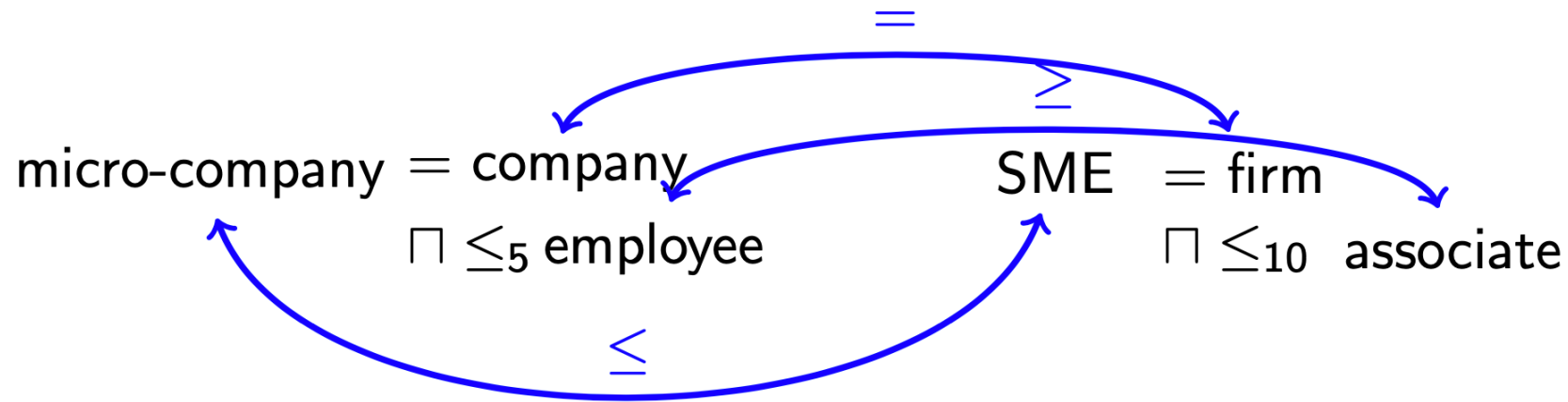
- **Graph-based**: consider ontologies as labelled graphs, assumption: if nodes are similar then their neighbours must be similar
- **Taxonomy-based**: consider only specialisation/generalization relation
- **Model-based**: take into account semantic interpretation of the ontologies, assumption: if two entities are the same then they share the same interpretation
- **Instance-based**: use individual representation of classes, i.e., classes are considered similar if they share many instances

Structure-level techniques: graph-based

- Children
 - Two non-leaf schema elements are structurally similar if their immediate children sets are highly similar
- Leaves
 - Two non-leaf schema elements are structurally similar if their leaf sets are highly similar, even if their immediate children are not
- Iterative fix point computation
 - If the neighbours of two nodes of the two ontologies are similar, they will be more similar

Structure-level techniques: model-based

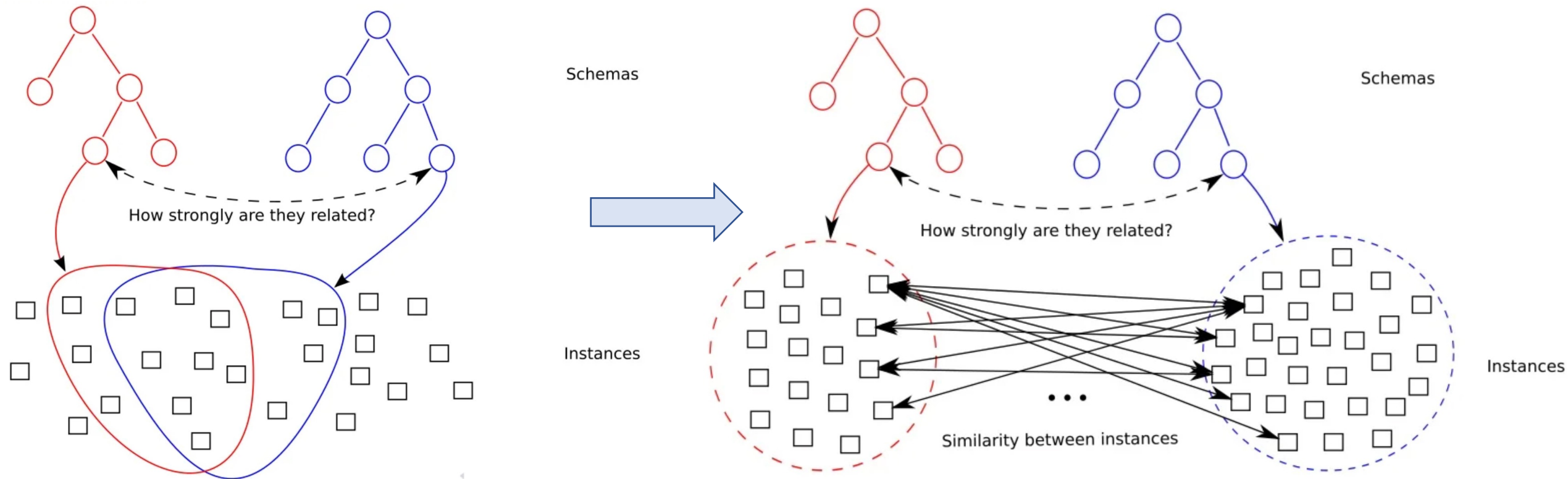
Description Logics (DL)-based



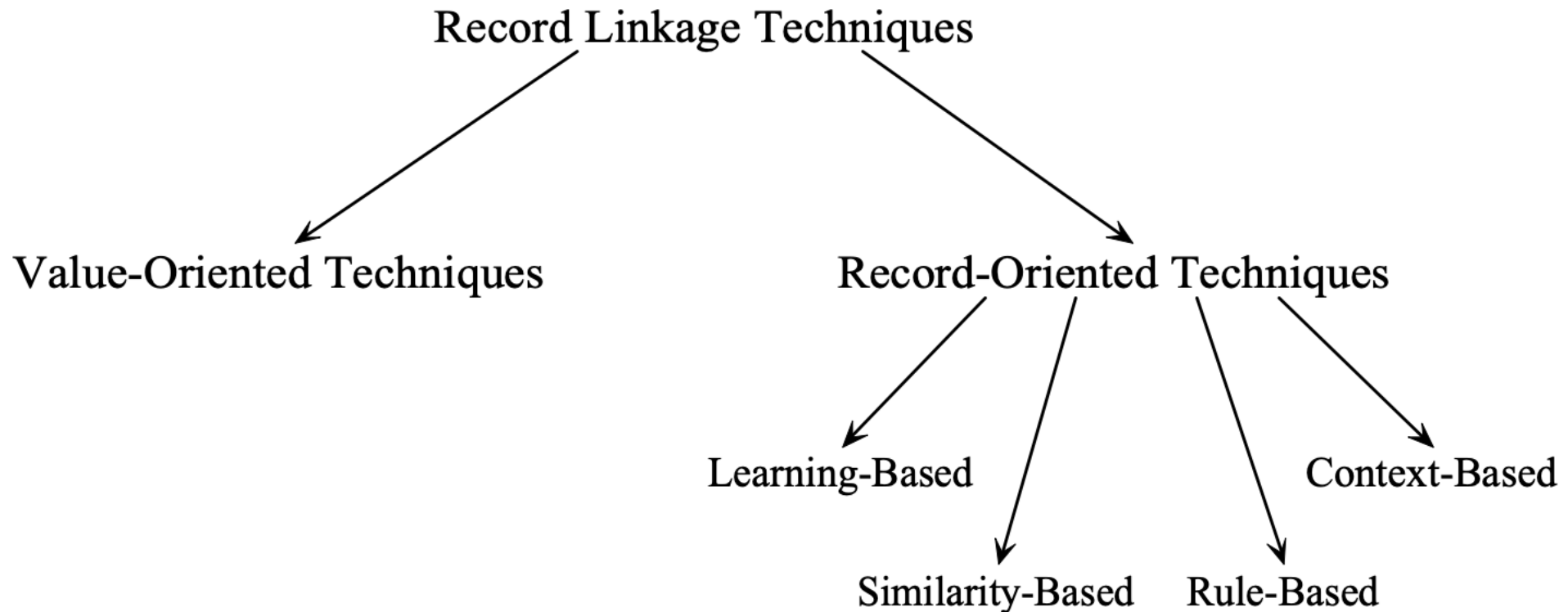
company = firm ; associate \sqsubseteq employee

micro-company \sqsubseteq SME

Structure-level techniques: instance-based



Instance matching (record linkage)



Value-oriented techniques

- **Assumption**: the similarity level of two records (entities) can be derived by matching the values of their comparable attributes
- Mostly focus on similarity of string attributes
 - Character-based: Edit Distance, Smith-Waterman Distance, Jaro Distance
 - Typographical variations, e.g. “organisation” vs “organization”
 - Token-based: Cosine similarity over TF-IDF vectors or word embeddings
 - Different conventions for describing data, e.g. “J.K. Rowling” vs “Rowling, J. K.”
 - Phonetic-based: Soundex, NYSIIS, Metaphone
 - Phonetic similarity, e.g. “Kageonne” vs “Cajun”

Classification of matching vs non-matching

- When the similarity of each pair of corresponding attribute values is computed, a decision engine is needed to classify whether two entities match or not
 - Learning-based
 - Similarity-based
 - Rule-based
 - Context-based

Learning-based techniques

- Supervised learning
 - Training data: a set of instance pairs and their expected classification (i.e. matching or non-matching records)
 - Non-trivial to get a high-quality and balanced training data set
 - Manually adding ambiguous cases if possible
- Unsupervised learning
 - Clustering record pairs with similar features that belong to the same class (i.e. matching or non-matching records)
- Combining different learning techniques

Similarity-based techniques

- Considering the input records as long attribute values
 - Concatenate all attribute values into one single string
- Average similarity of each pair of corresponding attribute values
 - Weighted average may better reflect domain knowledge
- Taking into account the frequency each value occurs
 - A matched “Paul Smith” counts less than the matched “Bamidele Melisizwe”

Rule-based techniques

- Instead of similarity values, a Boolean output is assigned
 - For example, if two records denoting books share the same value on attributes “Title”, “Author” and “Publication year”, there is a very high probability that the considered records refer to the same book.

Context-based techniques

- Taking into account the relationships between records
 - For example, matching clusters of records instead of individual records

Optimisation

- Reduction of the number of comparisons
 - **Blocking**: dividing instances in homogeneous and mutually exclusive *blocks* and comparing only with instances belonging to the same block
 - **Sorted neighbourhood**: sorting instances according to the value they assume on the property with the highest discriminating power and only comparing instances within a shifting- window of a fixed dimension
- Reduction of the cost of each comparison
 - Only a subset of the corresponding attribute values matters
 - E.g. title-author-year is a reasonable subset to distinguish books

Similarity filter and alignment extraction

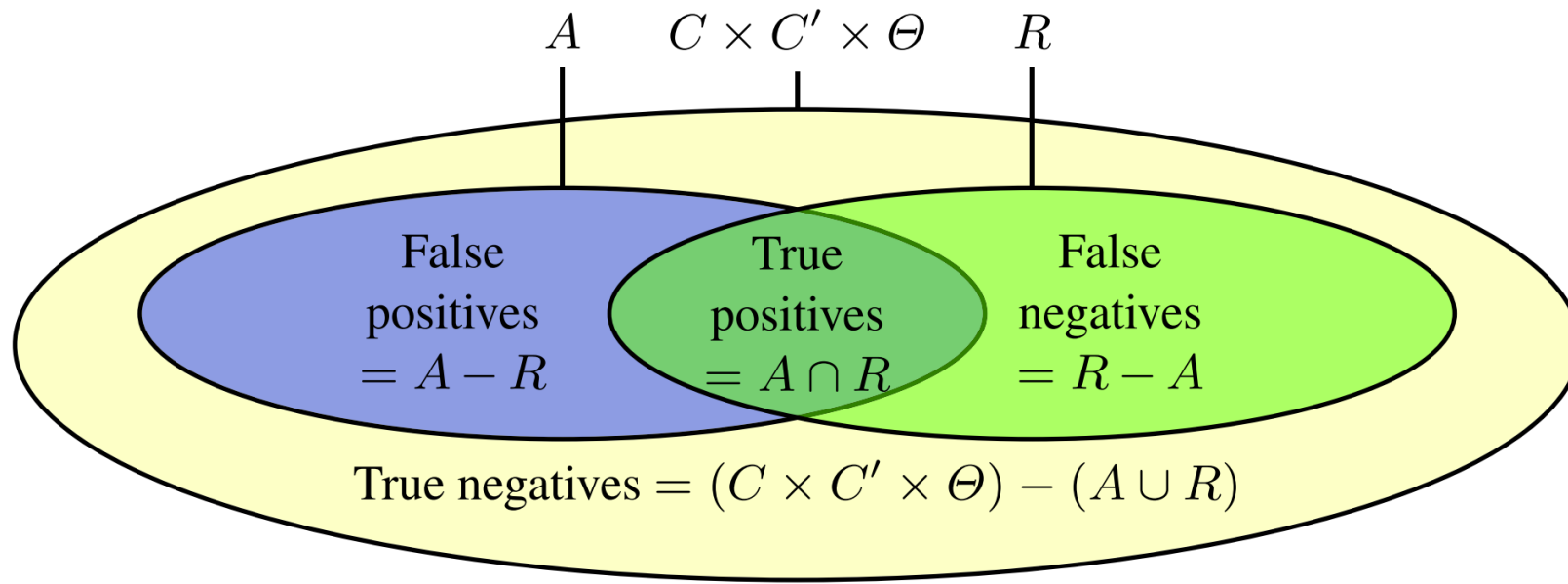
- Many algorithms are based on similarity or distance computation. A few operations can be based on similarity/distance matrices.
- Various thresholding options to filter similarities
 - **Hard threshold** retains all the correspondence above threshold n ;
 - **Delta threshold** consists of using as a threshold the highest similarity value out of which a particular constant value d is subtracted;
 - **Gap threshold** retains the correspondences ordered by decreasing similarity until the difference in similarity between two correspondences becomes larger than n ;
 - **Proportional threshold** consists of using as a threshold the percentage of the highest similarity value;
 - **Percentage** retains the $n\%$ correspondences above the others.

Evaluation

Alignment quality measures

- **Quality measures** are the intrinsic measures of the alignment (they do not depend on any reference):
 - threshold on confidence or average confidence,
 - cohesion measures between matched entities, i.e., their neighbours are matched with each other,
 - ambiguity degree, i.e., proportion of classes matched to several other classes,
 - agreement or non-disagreement between the aligned ontologies,
 - violation of some constraints, e.g., acyclicity in the correspondence paths,
 - satisfaction of syntactic anti-patterns,
 - consistency and coherence.

Evaluation with a reference alignment



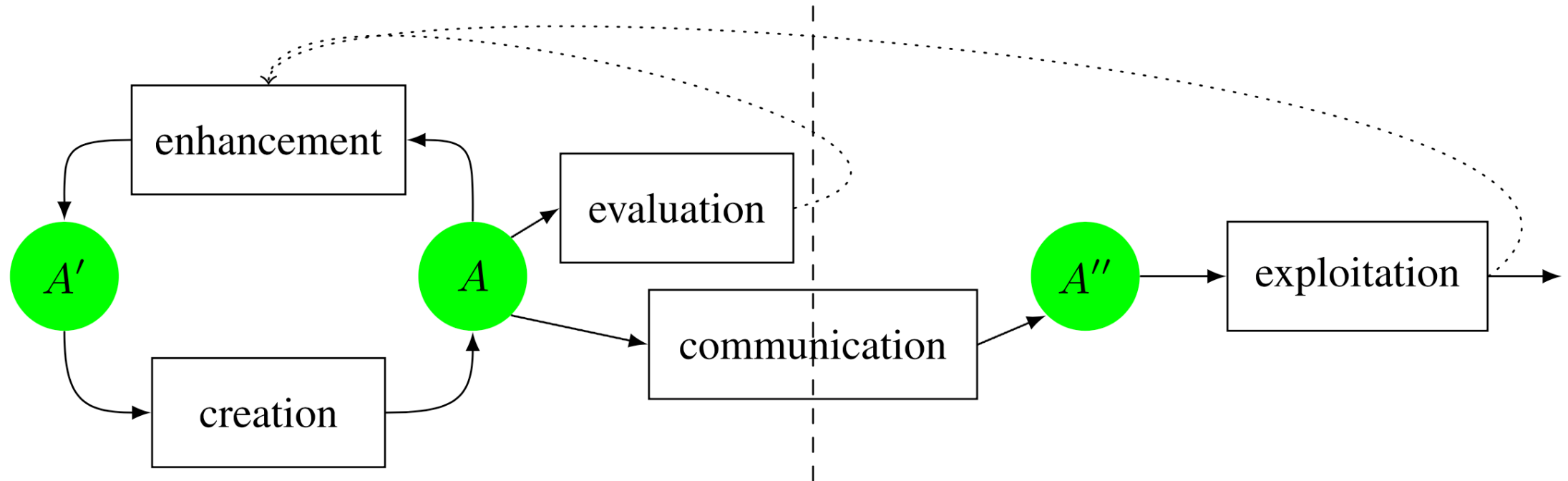
- **Precision** measures the ratio of correctly found matches (true positives) over the total number of returned matches (true positives and false positives)
- **Recall** measures the ratio of correctly found matches (true positives) over the total number of expected matches (true positives and false negatives)
- **F-measure** = $2 * P * R / (P + R)$

Evaluation without a reference alignment

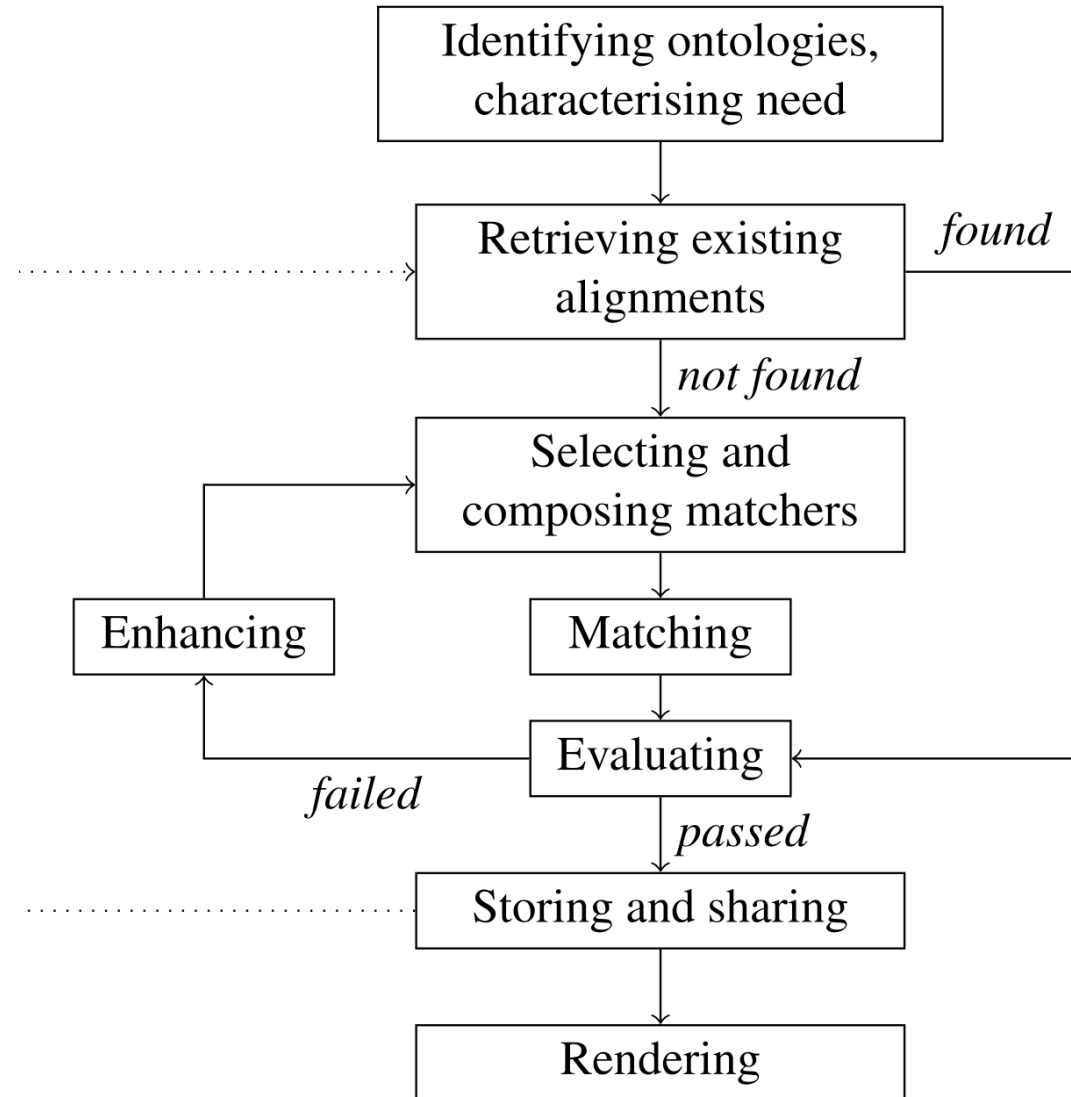
- **Sampling** or **pooling**-based evaluation
 - Build a subset of alignment using sampling or pooling
 - Expert evaluation
- **End-to-end** evaluation
 - Testing the quality of alignment using an application
- **Performance** measures
 - Speed, memory, scalability

Alignment lifecycle

The alignment life cycle



The matching methodology workflow



Learning and tuning

- A multi-strategy **learning** approach is useful when several learners are used, each one handling a particular kind of pattern that it learns best.
- **Tuning** refers to the process of adjusting a matcher for a better functioning in terms of:
 - better **quality** of matching results, measured, e.g., through precision or F-measure, and
 - better **performance** of a matcher, measured through resource consumption, e.g., execution time, main memory.

Summary

- Heterogeneity of ontologies is in the nature of the semantic web;
- Ontology matching is part of the solution;
- It can be based on many different techniques;
- Iterative process towards improved performance;
- There remain serious challenges ahead.

Challenges

- Large-scale and efficient matching,
- Matching with background knowledge,
- User involvement,
- Multilinguality,
- Social and collaborative matching,
- Uncertainty in matching,
- Reasoning with alignments,
- Alignment management.
- ...