1 Managing Semantic Data

Overview

Contents

1.1 Ontology and Ontology Learning

Basics

- Applications with ontology
- Jim Hendler: “a little semantic goes a long way”
- Availability, suitability, completeness

Ontology Definition

What is ontology?

- ”Specification of a conceptualization” Tom Gruber
- ”A description of things that exist and how they relate to each other” Chris Welty

Ontology components

What are the components of the ontology?

Ontology can be defined as a tuple:

$$\vartheta = (C, R, H^C, rel, A^\vartheta)$$

- C is the set of ontology concepts. The concepts represent the entities of the domain being modeled. They are designated by one or more natural language terms and are normally referenced inside the ontology by a unique identifier.
- $H^C \subseteq C \times C$ is a set of taxonomic relationships between the concepts. Such relationships define the concept hierarchy.

Manual ontology creation is expensive

- R is the set of non-taxonomic relationships. The function $rel : R \to C \times C$ maps the relation identifiers to the actual relationships.
- A^{ϑ} is a set of axioms, usually formalized into some logic language. These axioms specify additional constraints on the ontology and can be used in ontology consistency checking and for inferring new knowledge from the ontology through some inference mechanism.

Ontology Learning

1.2 Methods of Ontology Learning

Layer-cake model

Layer-cake model for learning ontology

$\forall x, y(sufferFrom(x, y) \to ill(x))$

cure (domain:Doctor, range:Disease)

is_a (Doctor, Person)

Disease := <I, E, L>

{disease, illness}

disease, illness, hospital

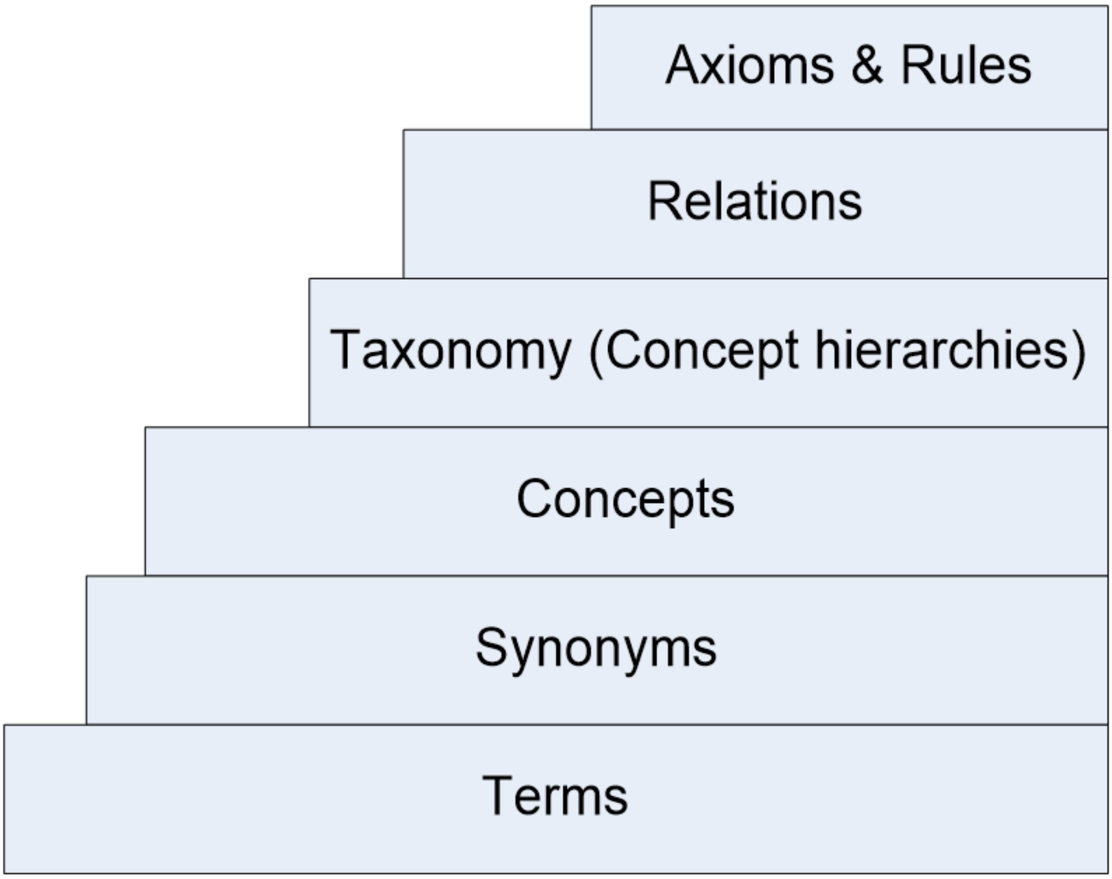
input

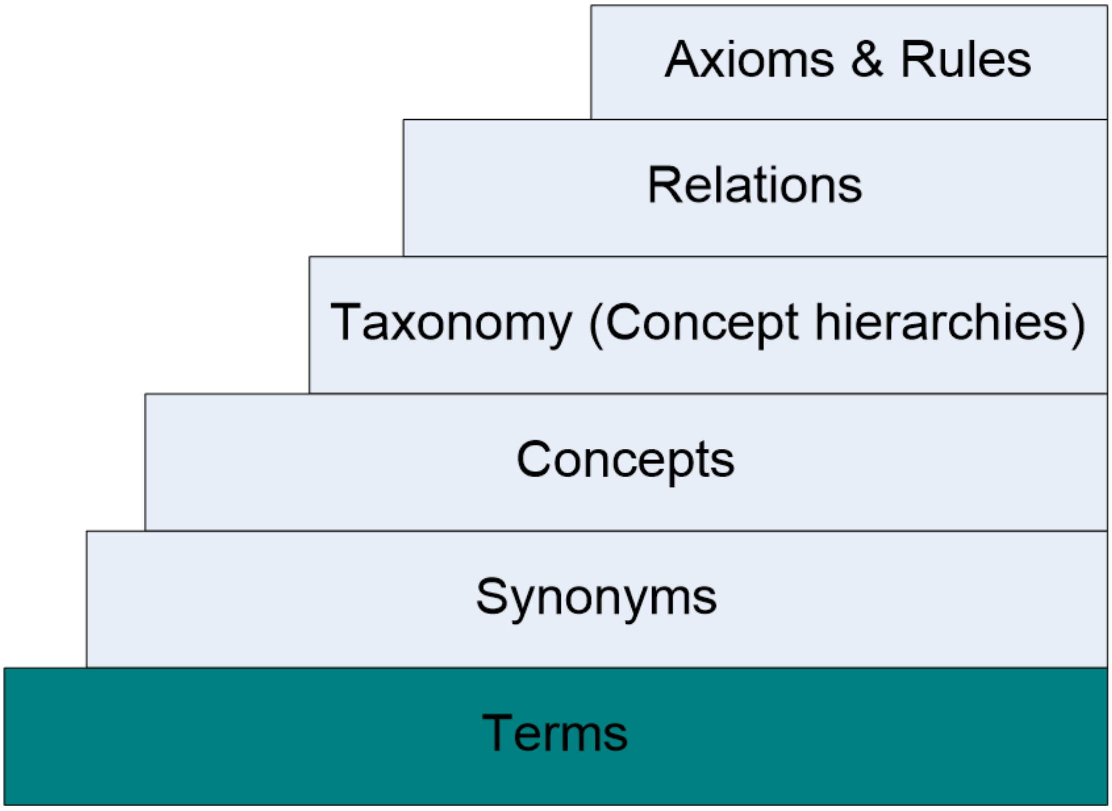
Possible input sources

- Structured data - database schemes
- Semi-structured data - dictionaries like **WordNet**
- Unstructured data - natural language text documents, like the majority of the HTML based web-pages

Learning methods

- Linguistic
- Statistical
- Rule-Based
- Logical


Axioms & Rules
Relations
Taxonomy (Concept hierarchies)
Concepts
Synonyms
Terms



Learning terms

Terms extraction

disease, illness, hospital

Terms extraction - Linguistic processing

Natural Language Processing (NLP), deep language analysis or information retrieval methods for term indexing.

- **Identifies** sentences, determined by periods or other punctuation marks
- **Tokenization** separates text into tokens which are the basic units

- **Normalizes** tokens to lower case to provide case-insensitive indexing
- **Stemming**: (fishing, fished, fisher) one stem: **fish**
- **Stop-words removing**: Meaningless tokens, **(there, so, other, etc..)**
- **POS tagging**: the **book** on the table (noun), to **book** a flight (verb)

Terms extraction - Statistical metrics

- **TF: Term Frequency**, how frequently a term occurs in **one document**.

  TF = (Number of times term t appears in a document / Total number of terms in the document)

- **IDF: Inverse Document Frequency**, how important a term is in the **corpus** IDF = log (Total number of documents / Number of documents with term t in it)

Terms extraction - Statistical metrics

$$tfidf(w) = tf(w).log(\frac{N}{df(w)})$$

The word is more popular when it appears several times in a document

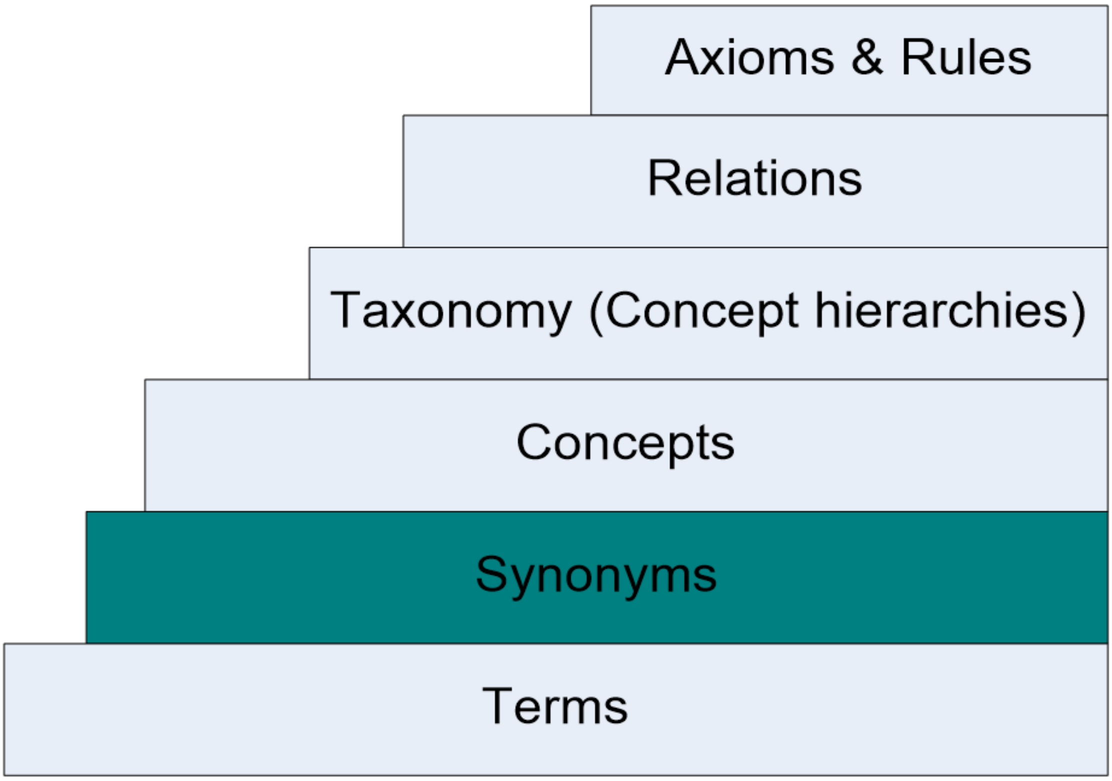
The word is more important if it appears in less documents

- $tf(w)$ → term frequency (number of words occurrences in a document)
- $df(w)$ → document frequency (number of documents containing the word
- N → number of all documents
- $tfidf$ → relative importance of the word in the document

Learning synonyms

Synonyms extraction

{disease, illness}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Synonyms extraction

Identification of terms that share semantics, i.e., potentially refer to the same concept

- Latent Semantic Indexing (LSI): Assumes that words that are close in meaning will occur in similar pieces of text (the distributional hypothesis).
- Wordnet

Synonyms extraction - Wordnet overview

What is wordnet?

- General lexical knowledge base
- Contains 150,000 words (noun, verb, adj, adv)
- A word can have multiple senses: "plant" as a noun has 4 senses
- Each concept (under each sense and PoS) is represented by a set of synonyms (a syn-set).
- Semantic relations such as hypernym/antonym/meronym of a syn-set are represented

Learning concepts

Concepts extraction

Disease := <I, E, L>

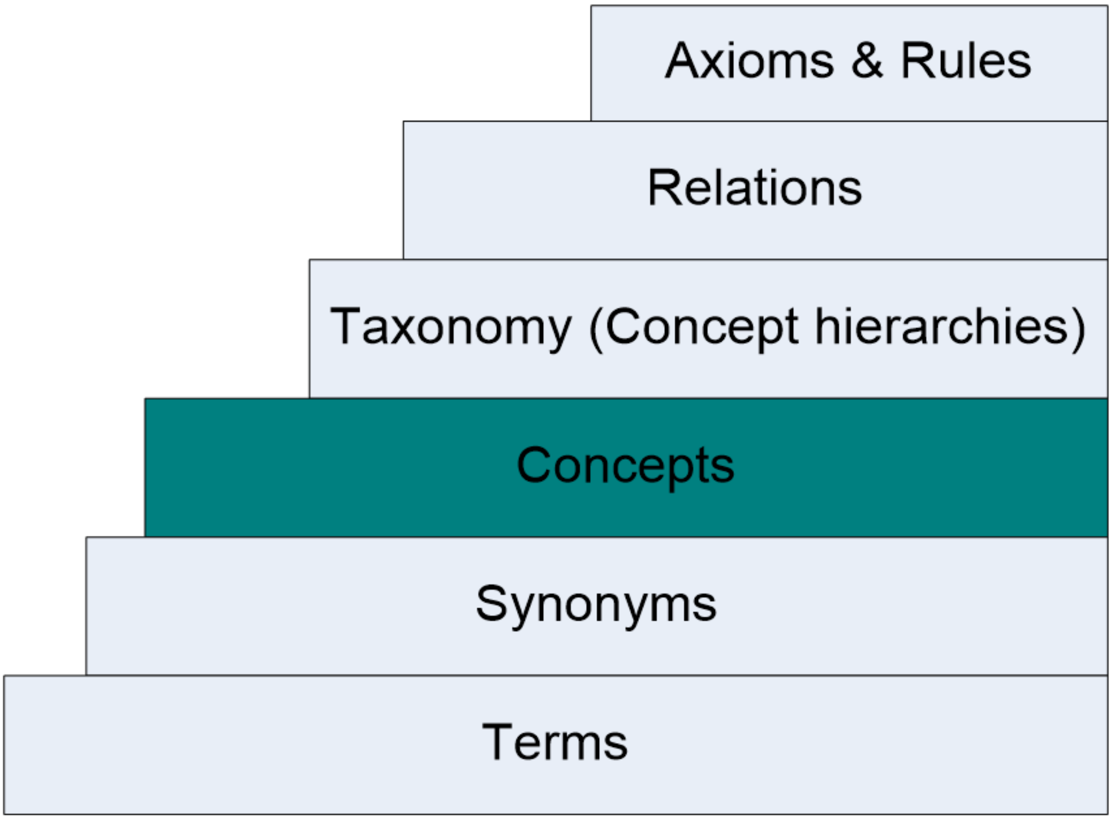
Concepts

Controversial as it is not clear what exactly constitutes a concept

A term may indicate a concept, if we define its:

- **Intension** (In)formal definition of the objects this concept describes *ex:* a disease is an impairment of health or a condition of abnormal functioning
- **Extension** Set of objects described by this concept (ontology population)

  ex: influenza, cancer, heart disease
- **Lexical Realizations** The term itself and its multilingual synonyms *ex:* disease, illness, maladie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Concepts forming approaches

The detection of synonyms can help to cluster terms to groups of terms sharing (almost) the same meaning, thus representing ontological classes.

- Learning the extension of concepts
  - Unsupervised hierarchical clustering techniques known from machine learning research Clusters of related terms (overlaps almost completely with *term* and *synonym* extraction)
  - **for example** ”all movie actors appearing on the Web”
- Learning the intension of concepts
  - Acquisition of informal definition Textual description,i.e.a gloss of the concept (ex. from Wordnet), normative document, etc.
  - Acquisition of formal definition Disovering formal constraints that define a class membership

Concepts labeling

Hearst's patterns

1. Find hypernym candidates for each class members
2. Then select the top candidate related to the largest number of class members

Web search

1. Proper query of concatenating the child concepts
2. Return top 10 results + NLP
3. Select the most frequent phrase

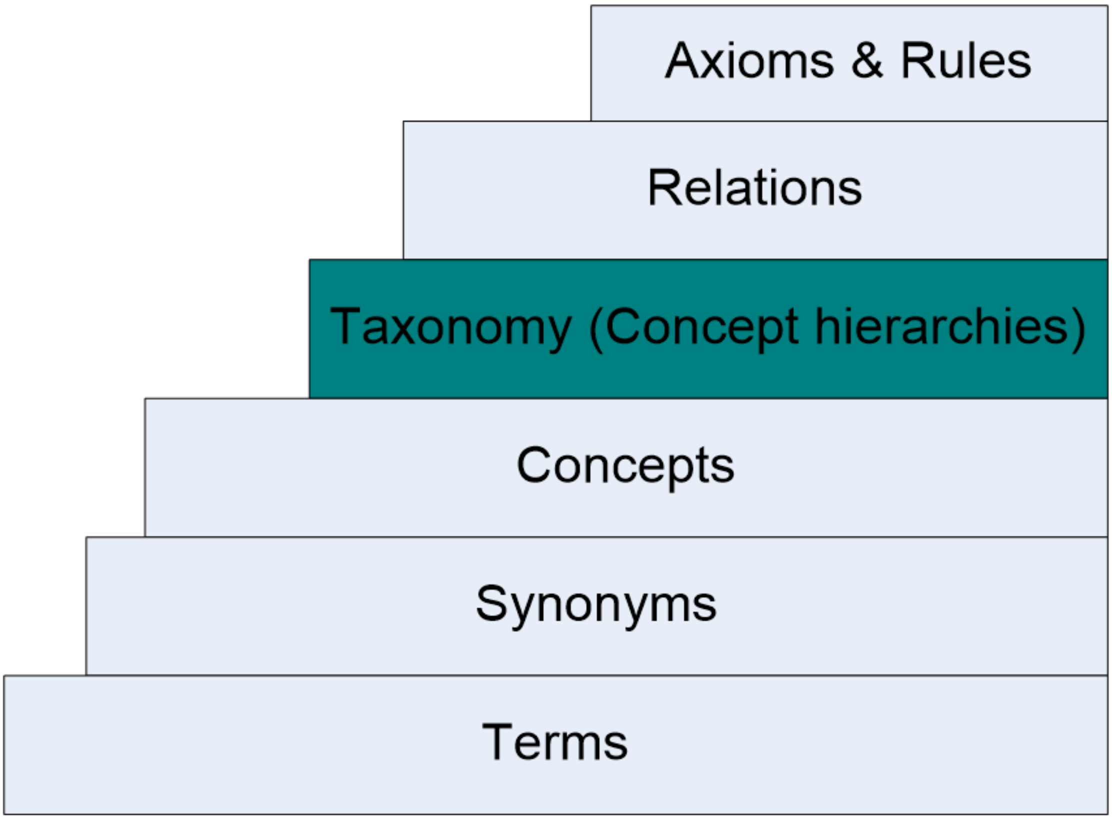
- Challenging problem
- Assign meaningful name to the newly-created parent node
- General enough to cover the scope of all the child concepts
- Specific enough to just cover that of them

Ex: *president* becomes the parent of concepts *Bush* and *Reagan.*

Learning concept hierarchies

Taxonomy

is_a (Doctor, Person)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Learning concept hierarchies

Taxonomy

"is-a" hierarchy on concepts

Existing approaches

1. Hearst Patterns (Lexico-syntactic patterns)
2. Hierarchical Clustering
3. Document-based subsumption

Taxonomy - Hearst Patterns

- The acquisition of hyponym lexical relations from text
- Uses a set of predefined lexico-syntactic patterns which:

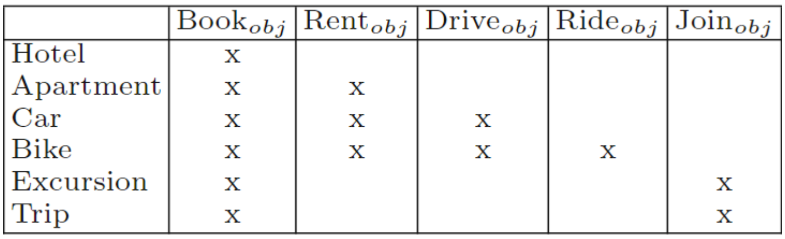
- Occur frequently and in many text genres - Indicate the relation of interest - Can be recognized with little or no pre-encoded knowledge

- Principle idea: match these patterns in texts to retrieve is-a relations
- Reasonable *precision*, very low *recall*

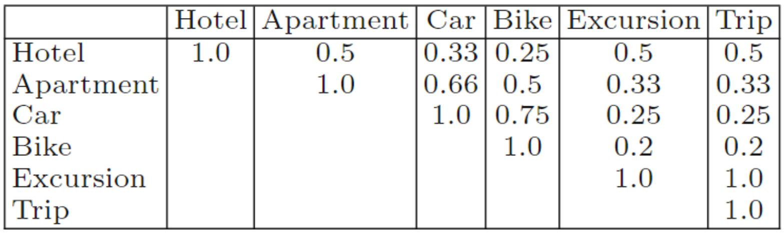
Taxonomy - Hearst Patterns

- Vehicles **such as** cars, trucks and bikes
- **Such** fruits **as** oranges or apples
- Swimming, running **and other** activities
- Swimming, running **or other** activities
- Publications, **especially** papers and books

- NP_{hyper} such as $\{NP_{hypo,}\}^*\{(and|or)\}NP_{hypo}$
- such NP_{hyper} as $\{NP_{hypo,}\}^*\{(and|or)\}NP_{hypo}$
- $NP_{hypo}\{,NP\}^*\{,\}$ or other NP_{hyper}
- $NP_{hypo}\{,NP\}^*\{,\}$ and other NP_{hyper}
- NP_{hyper} especially $\{NP_{hypo,}\}^*\{(and|or)\}NP_{hypo}$



	Book_{obj}	Rent_{obj}	Drive_{obj}	Ride_{obj}	Join_{obj}
Hotel	x				
Apartment	x	x			
Car	x	x	x		
Bike	x	x	x	x	
Excursion	x				x
Trip	x				x



	Hotel	Apartment	Car	Bike	Excursion	Trip
Hotel	1.0	0.5	0.33	0.25	0.5	0.5
Apartment		1.0	0.66	0.5	0.33	0.33
Car			1.0	0.75	0.25	0.25
Bike				1.0	0.2	0.2
Excursion					1.0	1.0
Trip						1.0

Taxonomy - Hierarchical Clustering

Jaccard coefficient distance $= |\frac{A \wedge B}{A \vee B}|$

Taxonomy - Hierarchical Clustering

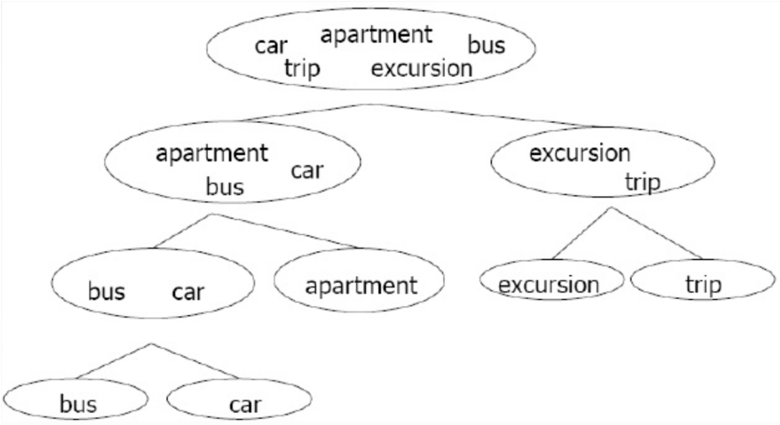
see [**staab2010handbook**]

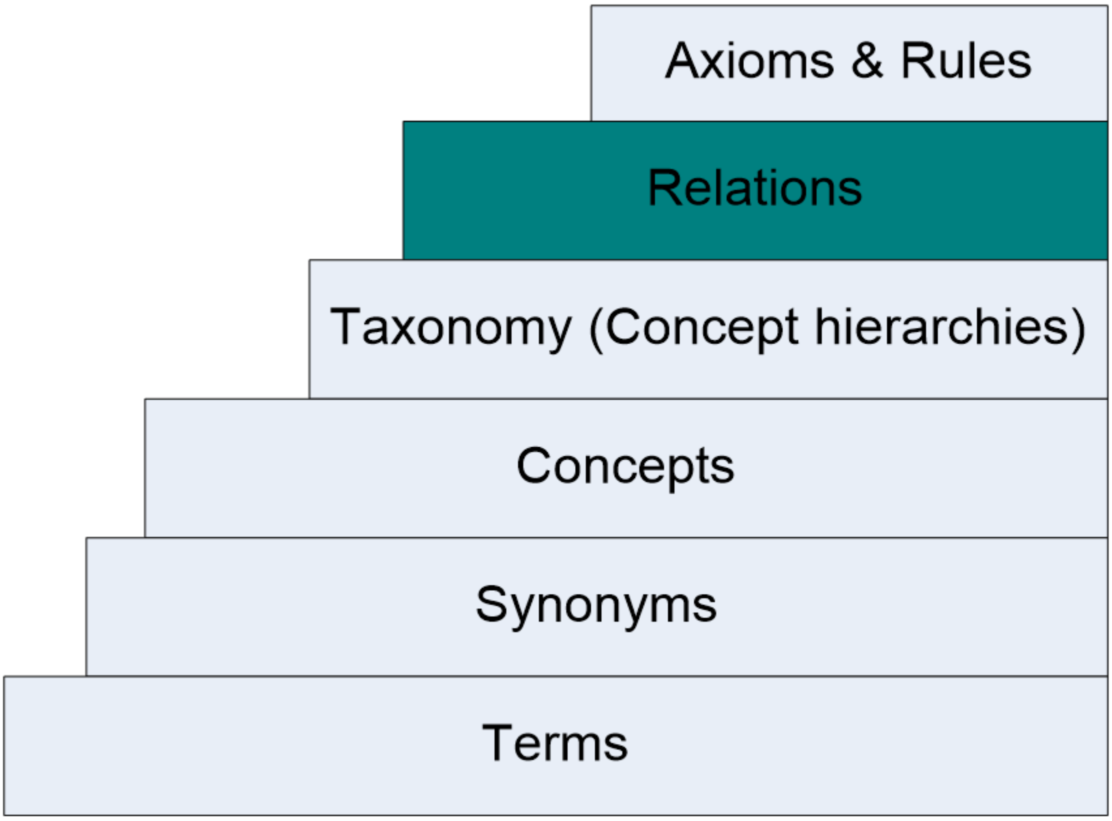
Taxonomy - Document-based subsumption

Term t_1 subsumes term t_2 [is-a(t2,t1)] if t_1 appears in all the documents in which t_2 appears

$$P(x|y) = \frac{n(x,y)}{n(y)}$$

Term x subsumes term y iff $P(x|y) = 1$, where
$n(x,y)$ → the number of documents in which x and y co-occur $n(y)$ → the number of documents that contain y





Learning relations

Relation extraction

cure (domain:Doctor, range:Disease)

Relation extraction - Specific Relations

Discover anonymous associations between words

- X consists of Y (part-of) **The framework for OL** consists of **information extraction**, **ontology discovery** and **ontology organization**
- X is used for Y (purpose) **OL** is used for **OE**
- X leads to Y (causation) **Good OL methods** lead to **good OE**

Relation extraction

OntoLT
Syntactic analysis: Maps a *subject* to the **domain**, the *predicate* or *verb* to **relation** and the *object* to its **range**.

The player kicked the ball to the net
relation: kick (domain: player, range: ball)

TextToOnto

$$love(man; woman) \wedge love(kid; mother) \wedge love(kid; grandfather)$$
$$\Rightarrow$$
$$love(person; person)$$

However, different verbs can represent *the same* (or a *similarTo*) relation Clustering → advise, teach, instruct

Learning rules and axioms

Rules and axioms extraction

$\forall x, y(sufferFrom(x, y) \rightarrow ill(x))$

Rule Extraction

DIRT - Discovery of Inference Rules from Text (Lin and Pantel, 2001)

- Let X be an algorithm which solves a problem Y
- Using similar constructions like **X solves Y**, **Y is solved by X**, **X resolves Y**
- $\forall x, y(solves(x, y) \Rightarrow isSolvedBy(y, x))$ (Inverse object property)
- $\forall x, y(solves(x, y) \Rightarrow resolves(x, y))$ (Equivalent object property)

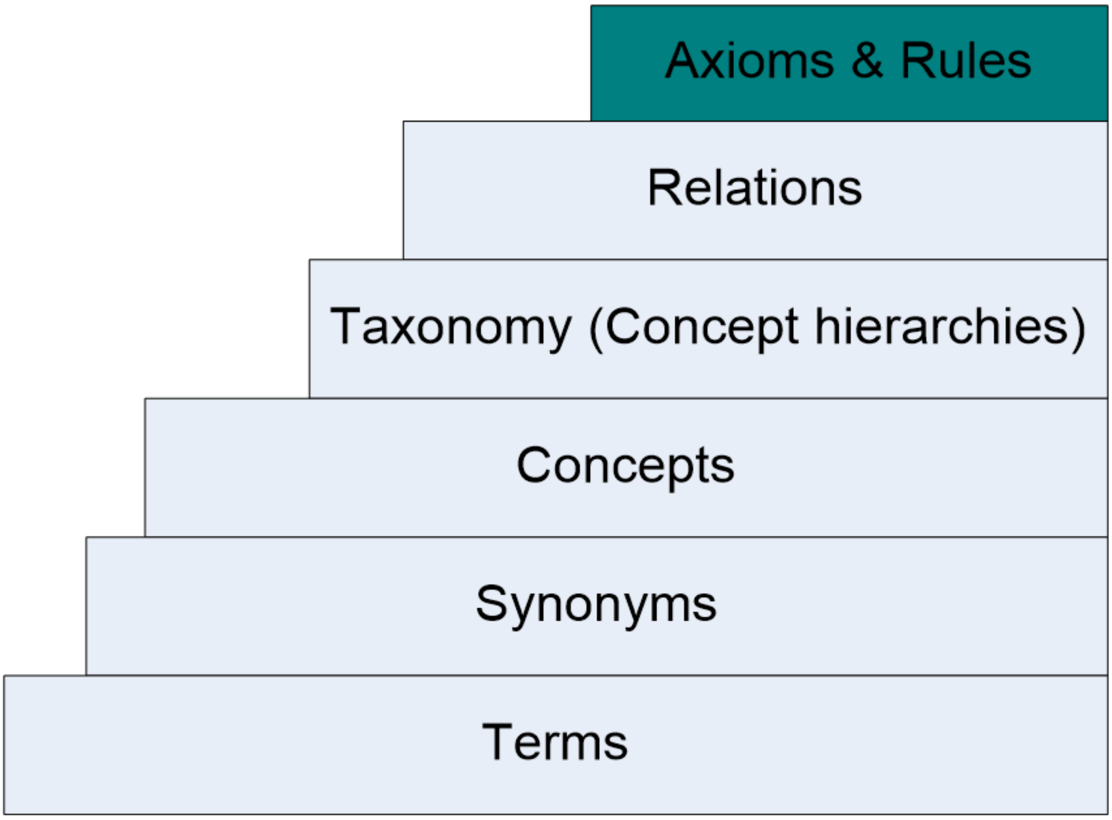
Axiom Extraction

- Automated Evaluation of Ontologies - AEON (Völker et al., 2008)

  Axioms are extracted (using lexico-syntatic patterns) from a Web Corpus

- Dealing with uncertainty and inconsistency (Haase and Völker, 2005)

  Disjointness axioms → disjoint(man,woman)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		Terms	Concepts	Taxonomic relations	Non-taxonomic relations	Axioms
statistic methods	Text pre-processing	X				
	POS tagging	X				
	Sentence parsing	X				
	Latent semantic		X			
	Cooccurrence	X	X			
	Clustering		X	X		
	Term subsumption			X		
	Association rules					
Linguistic methods	Seed words	X				
	Semantic lexicon		X	X	X	
	Sub-categorization frames	X	X			
	Syntactic structure	X			X	
	Dependency analysis	X			X	
	Semantic templates			X	X	
	Lexico-syntactic paterns			X	X	
	Axiom templates					X
Logical methods	Logical inference			X	X	
	Inductive Logic					X

Table 1.1: Ontology learning tasks and subtasks and the state-of-art techniques applied for each

1.3 Ontology Evaluation

Quality criteria

- **Accuracy** Does the ontology accurately model the domain?
- **Adaptability** Can the ontology easily be adapted to various uses?
- **Clarity** Is the meaning implied by the ontology clear?
- **Completeness** Does the ontology richly or thoroughly cover the domain?
- **Computational efficiency** How easily can automatic reasoners perform typical tasks?
- **Conciseness** Does the ontology include unnecessary axioms or assumptions?
- **Consistency** Does the ontology lead to logical errors or contradictions?
- **Organisational fitness** Is the ontology easily deployed in the application context? Is it easy to access? Does it align to other ontologiesalready in use?

How to evaluate OL

- Benchmark corpora and ontologies
- Evaluation of methods using different information sources

1.4 Ontology Learning Tools

The *festival* **attracts** *culture* vultures to see live drama, dance and music

OntoLT

- *festival* and *culture* are class candidates - using statistical analysis (TF-IDF)
- **attracts** is a relation between festival and culture - using NLP

ASIUM - Acquisition of Semantic knowledge Using ML Methods

- Taxonomic relations among terms in technical texts
- Conceptual Clustering

OntoLearn

- Enrich a domain ontology with concepts and relations
- NLP and ML

Text-To-Onto

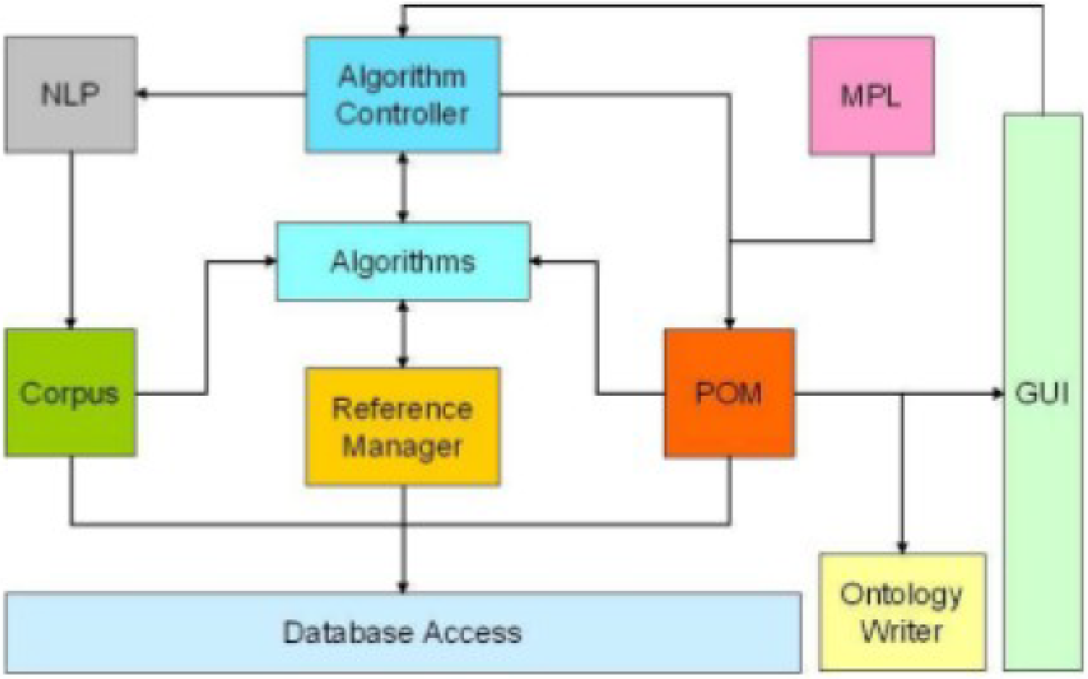
- Find taxonomic and non-taxonomic relations
- Statistics, Pruning Techniques and Association Rules
- Sucessor: Text2Onto tool

Text2Onto

- Ontology learning from textual documents **framework**
- System calculates a **confidence** for each learned object for better user interaction
- **Updates** the learned knowledge each time the corpus is changed and avoid processing it by scratch
- Interaction with end-users which is the central part of the architecture.
- Allows for easy
  1. combination of algorithms,
  2. execution of algorithms,
  3. writing new algorithms

Text2Onto requirements

- Java 6 +
- WordNet
- GATE (General Architecture for Text Engineering)



Text2Onto components

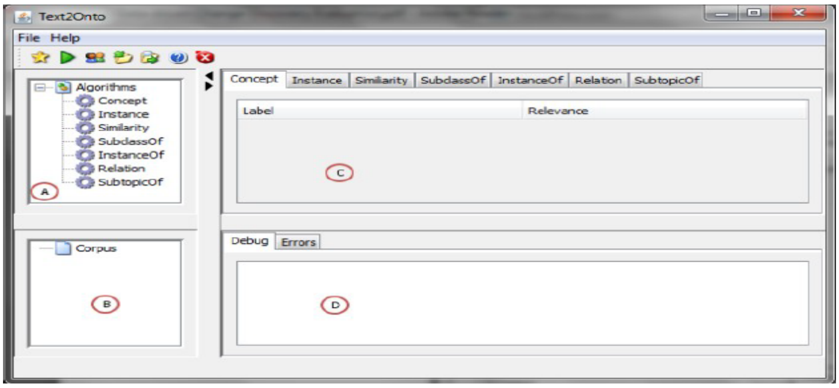
- NLP engine
- Algorithms
- Algorithm Controller
- (Probabilistic Ontology Model) POM

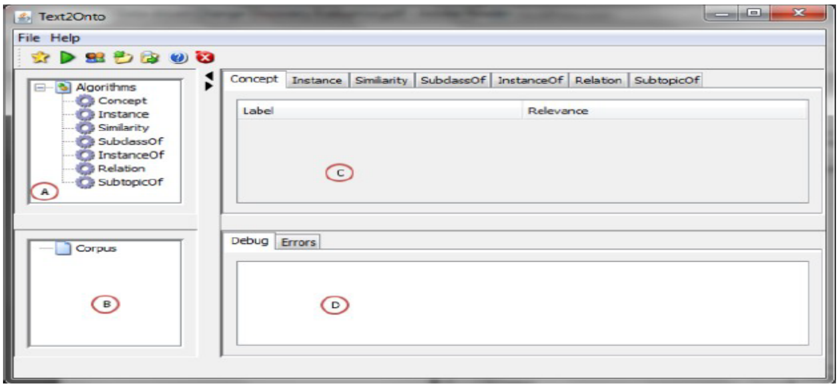
POM

container for learned objects. All objects are enhanced by calculated probabilities in such manner that a user can decide whether to include this object into the ontology or not.

Text2Onto workflow

- **(A) Controller view** where we specify which Algorithms to use and how to combine the results of these algorithms.
- **(B) Corpus view** from where adding / removing a corpus is done.





Text2Onto workflow

- **(C) POM view panel**. Displays the results of the current ontology learning process.
- **(D) Displays** debugging messages and error messages.

Text2Onto workflow

Step 1 - Add a Corpus

Right-click on the label *Corpus* on corpus view panel and add a corpus.

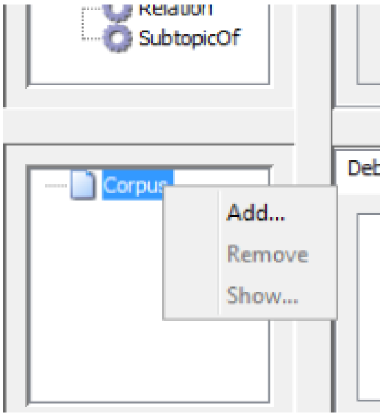
Text2Onto workflow

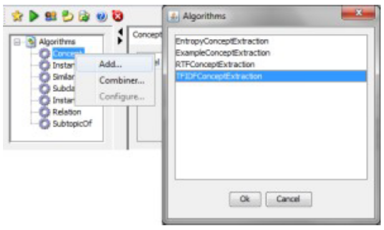
Step 2 - Specify algorithms to be applied

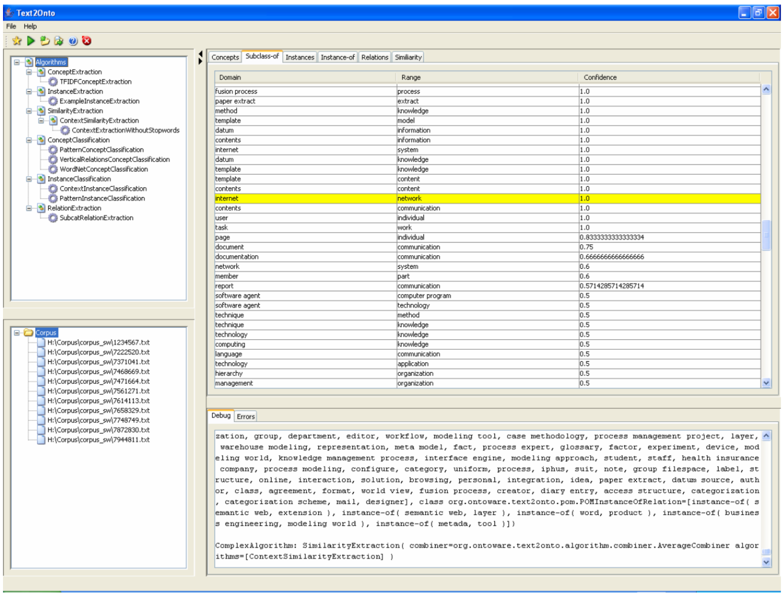
Right-click on the required entity on the controller view panel and click **add**. A list of available algorithms will appear. You can add one or more algorithms from here.

Step 3 - Run

Once all required algorithms have been specified, click the **Run** icon






Text2Onto
File
Help
Algorithms
ConceptExtraction
TFIDFConceptExtraction
InstanceExtraction
ExampleInstanceExtraction
SimilarityExtraction
ContextSimilarityExtraction
ContextExtractionWithoutStopwords
ConceptClassification
PatternConceptClassification
VerticalRelationsConceptClassification
WordNetConceptClassification
InstanceClassification
ContextInstanceClassification
PatternInstanceClassification
RelationExtraction
SubcatRelationExtraction
Corpus
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H:\Corpus\corpus_sw\7222520.txt
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H:\Corpus\corpus_sw\7872830.txt
H:\Corpus\corpus_sw\7944811.txt
Concepts
Subclass-of
Instances
Instance-of
Relations
Similiarity
Debug
Errors

Domain	Range	Confidence
fusion process	process	1.0
paper extract	extract	1.0
method	knowledge	1.0
template	model	1.0
datum	information	1.0
contents	information	1.0
internet	system	1.0
datum	knowledge	1.0
template	knowledge	1.0
template	content	1.0
contents	content	1.0
internet	network	1.0
contents	communication	1.0
user	individual	1.0
task	work	1.0
page	individual	0.8333333333333334
document	communication	0.75
documentation	communication	0.6666666666666666
network	system	0.6
member	part	0.6
report	communication	0.5714285714285714
software agent	computer program	0.5
software agent	technology	0.5
technique	method	0.5
technique	knowledge	0.5
technology	knowledge	0.5
computing	knowledge	0.5
language	communication	0.5
technology	application	0.5
hierarchy	organization	0.5
management	organization	0.5

```
zation, group, department, editor, workflow, modeling tool, case methodology, process management project, layer,
 warehouse modeling, representation, meta model, fact, process expert, glossary, factor, experiment, device, mod
eling world, knowledge management process, interface engine, modeling approach, student, staff, health insurance
 company, process modeling, configure, category, uniform, process, iphus, suit, note, group filespace, label, st
ructure, online, interaction, solution, browsing, personal, integration, idea, paper extract, datum source, auth
or, class, agreement, format, world view, fusion process, creator, diary entry, access structure, categorization
, categorization scheme, mail, designer], class org.ontoware.text2onto.pom.POMInstanceOfRelation=[instance-of( s
emantic web, extension ), instance-of( semantic web, layer ), instance-of( word, product ), instance-of( busines
s engineering, modeling world ), instance-of( metada, tool )]}

ComplexAlgorithm: SimilarityExtraction( combiner=org.ontoware.text2onto.algorithm.combiner.AverageCombiner algor
ithms=[ContextSimilarityExtraction] )
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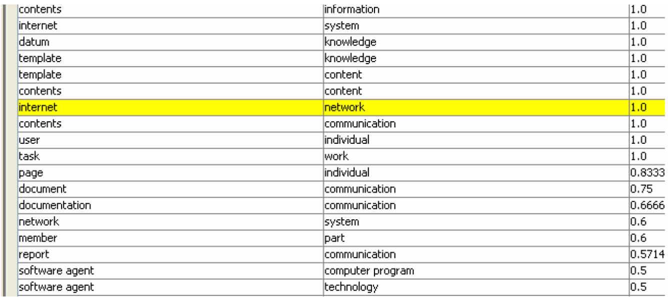

contents	information	1.0
internet	system	1.0
datum	knowledge	1.0
template	knowledge	1.0
template	content	1.0
contents	content	1.0
internet	network	1.0
contents	communication	1.0
user	individual	1.0
task	work	1.0
page	individual	0.8333
document	communication	0.75
documentation	communication	0.6666
network	system	0.6
member	part	0.6
report	communication	0.5714
software agent	computer program	0.5
software agent	technology	0.5

Text2Onto workflow

The results will appear on the POM view panel (C).

Text2Onto workflow

Step 4 - Review the results
The results of Text2Onto may need to be filtered. We can do this by giving feedback to it. To give feedback, right-click on the required entity, go to feedback and set the appropriate feedback (True, False or Don't know).

Export the results
Results can be exported in KAON, RDFS or OWL format. To do this, go to File and click Export.

Text2Onto

Can Text2Onto **automatically** build an ontology by learning on a corpus of texts?

Can Text2Onto help a user to build an ontology?

FRED

- Transforms natural language text into RDF/OWL with linked data support
- Based on ontology design patterns
- Graph visualization
- Export the RDF result: RDF/XML, Turtle, N3, etc.
- Tasks:
  - Entity linking to Semantic Web data
  - Relation extraction between frames, events, concepts and entities
  - Negation representation
  - Temporal relation extraction
  - ... more

1.5 Conclusion

- We need to build Ontology quickly, easily and they have to be reliable!
- Fully automated OL system that works perfectly, doesn't exist **YET**
- User revision and interaction is essential
- Methods are based mainly on NLP techniques complemented with statistical measures

Ontology Learning is the old new era of developing ontologies. It is linked with many CS fields and it is all about understanding the reality through the structure of things