# Ontologies and Ontology Engineering

### Kristian Stavåker and Dag Sonntag VT 2011

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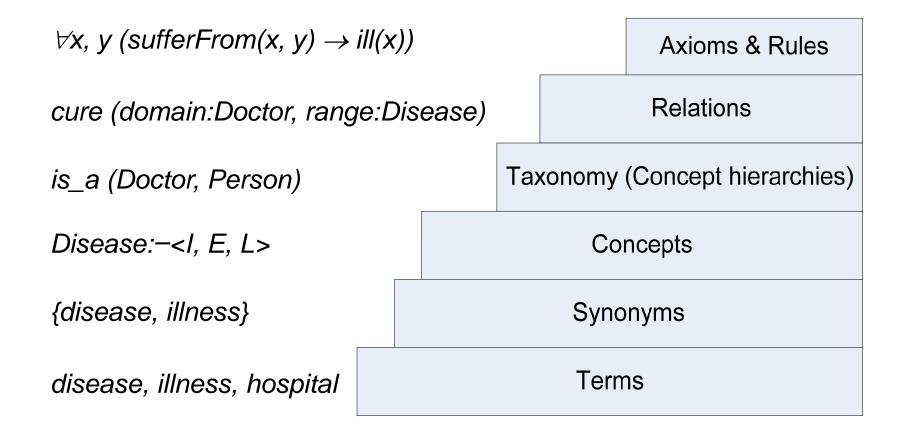
### Summary

- Wikipedia:
  - "Ontology learning (ontology extraction, ontology generation, or ontology acquisition) is a subtask of information extraction. The goal of ontology learning is to (semi-)automatically extract relevant concepts and relations from a given corpus or other kinds of data sets to form an ontology."
- Paul Buitelaar et al. / Ontology Learning from Text: An Overview [3]:
  - "The process of defining and instantiating a knowledge base is referred to as knowledge markup or ontology population, whereas (semi-)automatic support in ontology development is usually referred to as ontology learning."

## Summary (2)

- A lot of the work in this area builds on work from natural language processing, artificial intelligence and machine learning.
- The *ontology layer cake* consists of the various subtasks (increasing in complexity) involved in ontology learning.

### The Ontology Learning Layer Cake



### Outline

- Background
- Terms
- Synonyms
- Concepts
- Concept Hierarchies
- Relations
- Rules
- Conclusions

Terms Synonyms Concepts Concept Hierarchies Relations Rules Conclusions

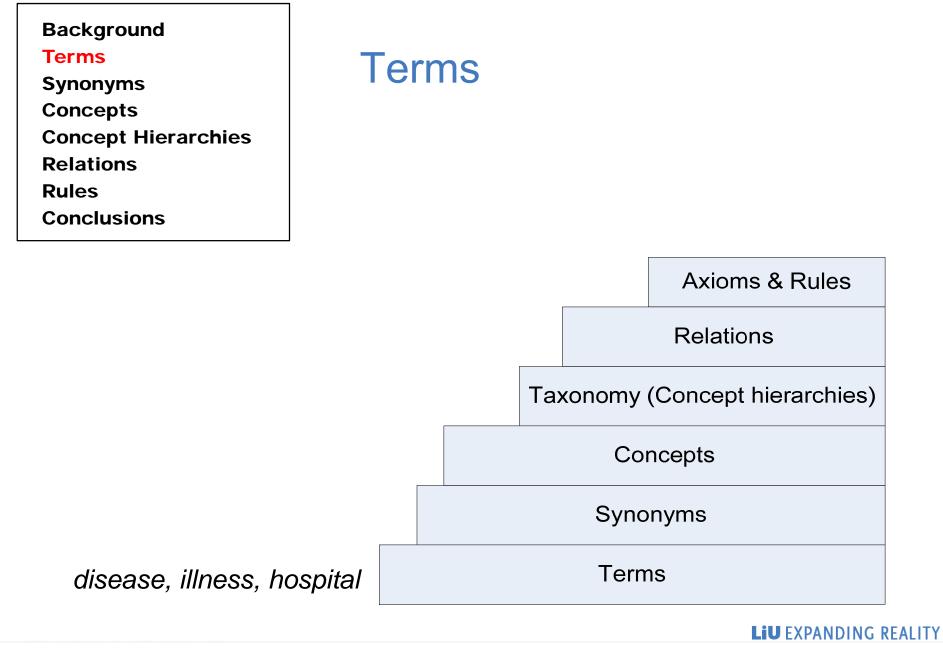
### Background

- Used for building an ontology from scratch through the application of a set of methods and techniques.
- The process of identifying terms, concepts, relations and optionally axioms from textual information to form an ontology.

Terms Synonyms Concepts Concept Hierarchies Relations Rules Conclusions

### Background (2)

- Unstructured sources (NLP techniques, morphological and syntactic analysis, etc.)
- Semi-structured sources (such as XML schema)
- Structured data (extract concepts and relations from for instance databases)



#### Terms

Synonyms Concepts Concept Hierarchies Relations Rules Conclusions

### Terms

- Term extraction is a prerequisite for all aspects of ontology learning from text.
- Term extraction implies more or less advanced levels of liguistic processing.
- An example of extracting relevant terms is counting frequencies of terms in a given set of documents (the corpus).

#### Terms

Synonyms

Concepts

**Concept Hierarchies** 

Relations

Rules

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Conclusions
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### Terms

• The computational linguistics community has proposed a wide range of more sophisticated techniques for term extraction.

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### Terms

- One common method:
  - A Part-Of-Speech (POS) tagger is run over the domain corpus
  - Possible terms are identified by constructing patterns, such as: Adj-Noun, Noun-noun, Adj-Noun-Noun, ... (names are ignored)
  - Apply statistical metrics in order to identify only the relevant to the text terms

Background Terms Synonyms Concepts Concept Hierarchies Relations Rules Conclusions	Term	S		
[[He SUBJ] [booked PRED] [[this] [table HEAD]NP:DOBJ:X1]] Discourse Analysis			Discourse Analysis	
[[It SUBJ:X1] [was PRED] still available…] [[He SUBJ] [booked PRED] [[this] [table HEAD] NP:DOBJ]S]			] Depe	endency Structure (S)
[[the SPEC] [large MOD] [table HEAD] NP]			-	dency Structure (Phrases)
[[the] [large] [table] NP] [[in] [the] [corner] PP]			Phrase Recognition	
[work~ing V]		Morphological Analysis (stemming)		
[table N:ARTIFACT] [table N:furniture]			Speech & S	emantic Tagging
[table] [2005-06-01] [John Smith] Tokenization (incl. Named-Entity Rec.)				

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Terms

Synonyms

Concepts

**Concept Hierarchies** 

Relations

Rules

Conclusions

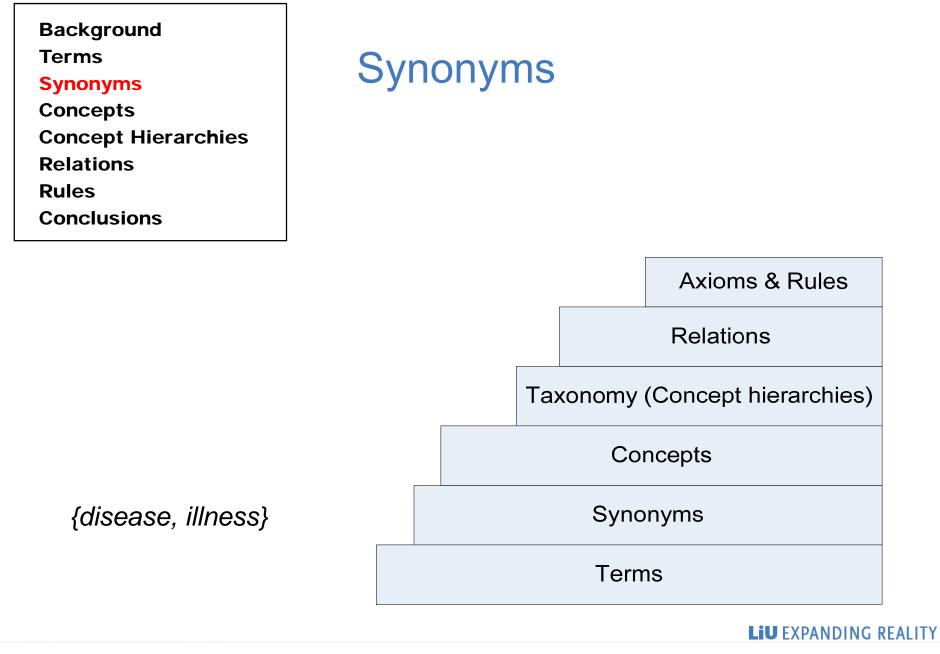
### Terms

- **Statistical Analysis** •
- Term Frequency Inverted Document • Frequency (TFIDF) - a popular weighting scheme

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

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13



Terms

#### **Synonyms**

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**Concept Hierarchies** 

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**Rules** 

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### Synonyms

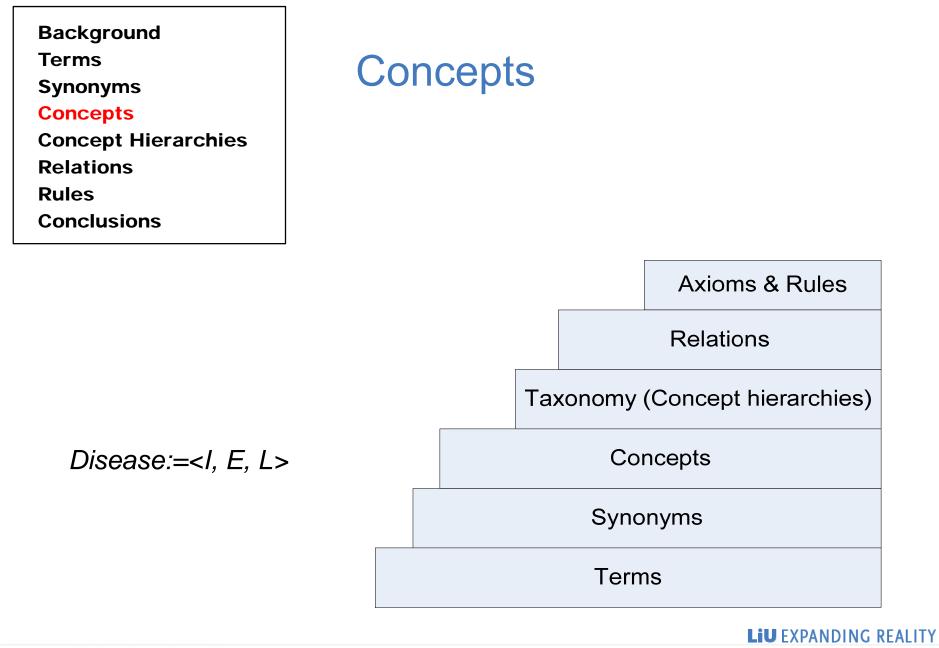
- Identification of terms that share semantics (potentially refer to the same concept)
- Methods for extracting synonyms
  - Based on WordNet/EuroWordNet
  - Harris' distributional hypothesis
  - Latent Semantic Indexing (LSI)
    - A NLP technique of analyzing relationships between a set of documents and the terms they contain

### Synonyms

• Pointwise Mutual Information measure for extracting synonyms.

$$PMI(x, y) \coloneqq \log_2 \frac{P(x, y)}{P(x)P(y)}$$

$$PMI_{Web}(x, y) \coloneqq \log_2 \frac{Hits(xANDy)MaxPages}{Hits(x)Hits(y)}$$



17

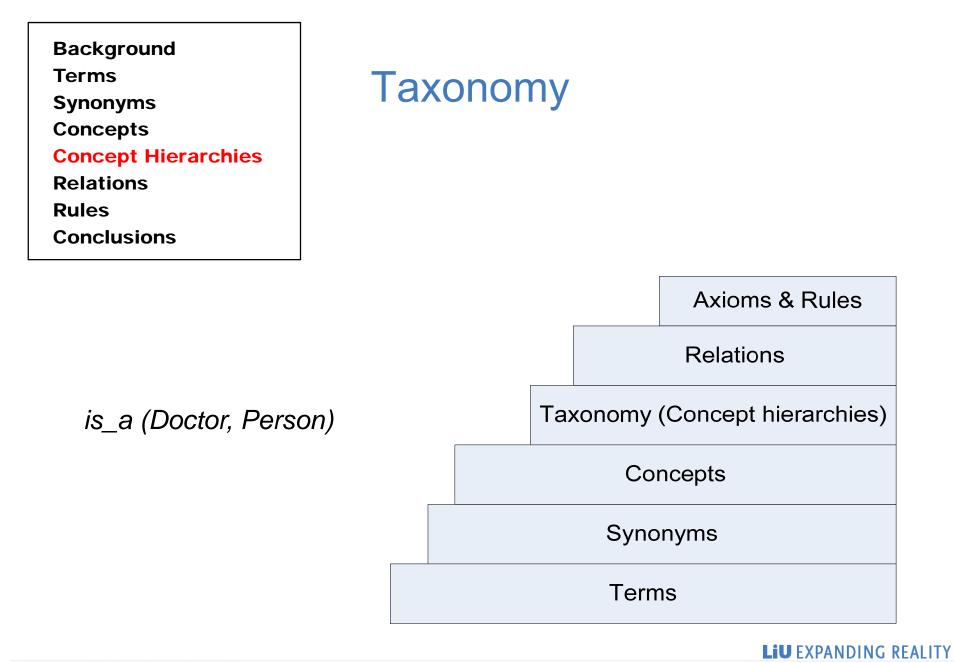
### Concepts

• Some confusion what extraction of concepts is since it is not clear what exactly constitutes a concept.

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## Concepts

- Intension (in)formal definition of the set of objects that this concept describes
  - Example: sound is a mechanical wave that is an oscillation of pressure composed of frequencies within the range of hearing
- Extension a set of objects that the definition of this concept describes
  - Example: music, noise, speech
- Lexical realizations the term itself and its multilingual synonyms
  - Example: sound, acoustics



그 지수는 물통 알끔 것 같아. 옷 옷에 다운 것이다.

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Relations

Rules

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### Taxonomy

- Simple ideas that work fairly well
  - Lexico-Synthatic Patterns (Hearst)
  - Formal Concept Analysis (FCA)
  - Phrase Analysis
  - WordNet
- These methods can be weightened together to get best results

# Lexico-Synthatic Patterns (Hearst)

- Hearst identified the following patterns
  - Hearst1: NPhyper such as {NPhypo,}\* {(and | or)} NPhypo
  - Hearst2: Such NPhyper as {NPhypo,}\* {(and | or)} NPhypo
  - Hearst3: NPhypo {,NP}\* {,} or other NPhyper
  - Hearst4: NPhypo {,NP}\* {,} and other NPhyper
  - Hearst5: NPhyper including {NPhypo,}\* NPhypo {(and | or)} NPhypo
  - Hearst6: NPhyper especially {NPhypo,}\* {(and | or)} NPhypo
- Example: "Vehicles such as bikes and cars"

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# Machine Readable Dictionaries

- Idea: Exploit the regularity of dictionaries like Wikepedia or Google definition
- Example: (from wikipedia)
  - Car: "An automobile, autocar, motor car or car is a wheeled motor vehicle used for transporting passengers, which also carries its own engine or motor. " => is(car, vehicle)

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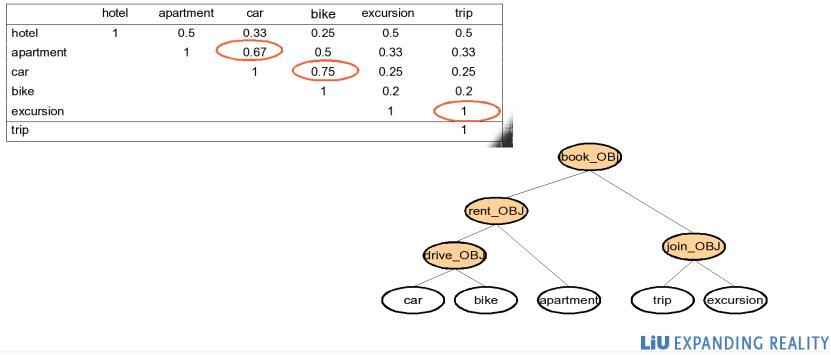
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# Formal Concept Analysis (FCA)

- Idea: Similar words share similiar attributes
- Example:



## **Phrase Analysis**

- Idea: Adjectives or Nominals in front of nouns in noun-phrases often indicate subclass
- Example: *Focal epilepsy* is a subclass of *epilepsy*

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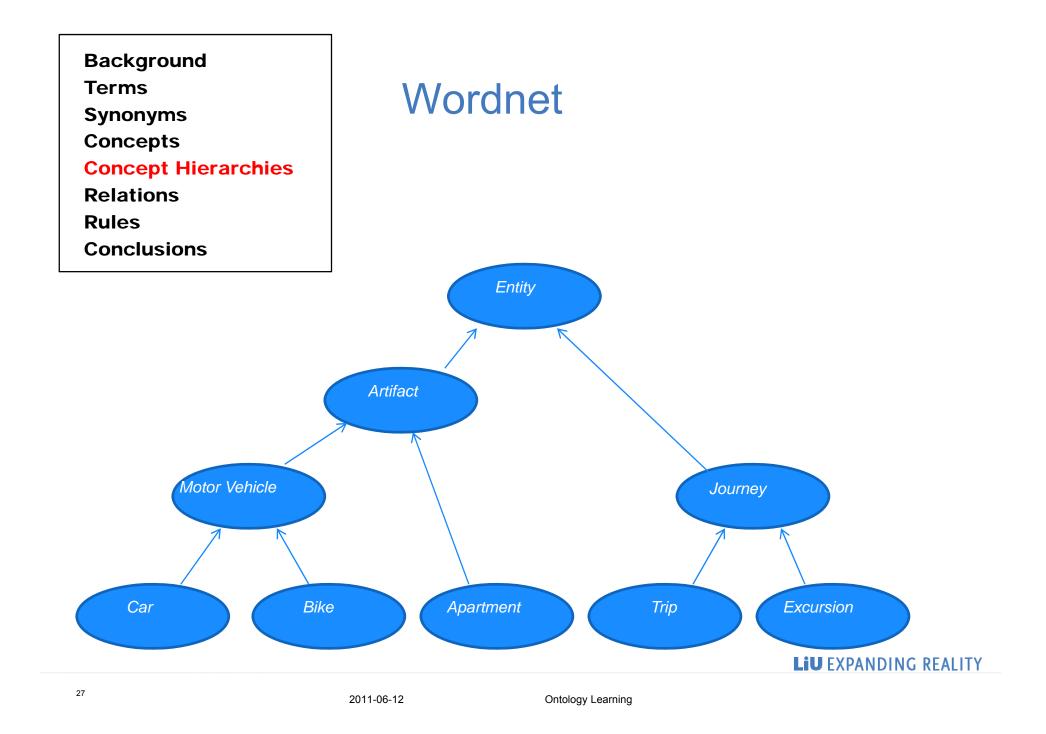
Relations

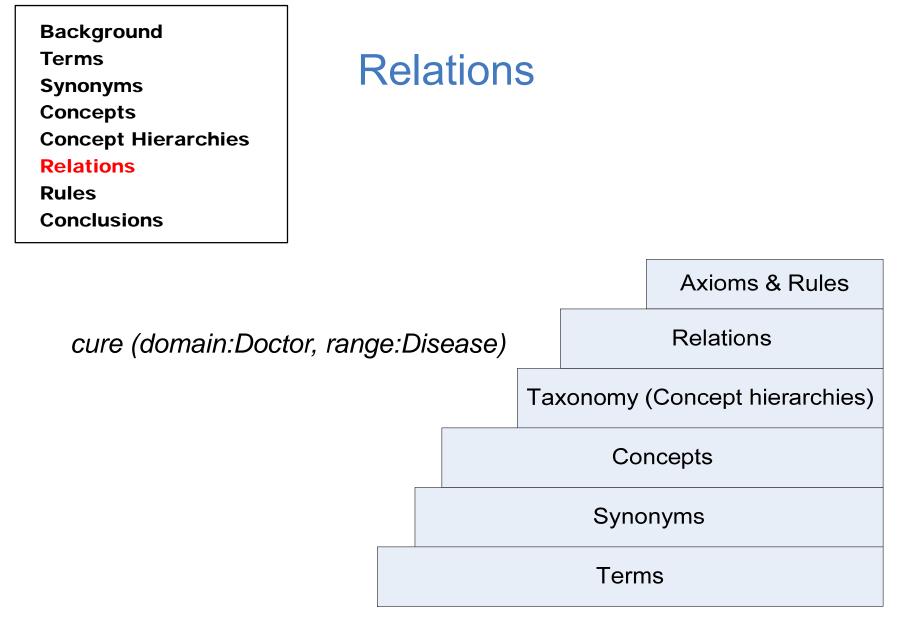
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### Wordnet

- Idea: Use already created ontologies
- WordNet contains ≈155000 words
  - Type (noun, verb and so on)
  - Their definition
  - Semantic synsets like
    - Hypernyms, hyponyms, meronyms, synonyms...





# Relations

- Can be found similar as concept hierarchies (is relation)
  - Lexico-Synthatic Patterns
  - Collocation Discovery
  - WordNet
- Specific relations
  - Part of (meronym)
- Attributes
  - Adjectives, e.g. color, weight and so on...

### Lexico-Synthatic Patterns

- Finds relations by searching after patterns of words
- E.g. The car has wheels =>, part-of(wheel, car) The car is red => is(car, red) or color(car,red) The car consists of wheels, engine, …

=> part-of(engine, car)...

• Hard to model every possible combination

### **Collocation Discovery**

- Idea: find words that occur together in a statistically significant manner
- Similar to the PCA-approach for the taxonomy
- The type of relation can then later be found by linguistic approaches
- Example: www-search for two concepts K1 and K2 using the Jaccard coefficient:

GoogleHits(Keyword1,Keyword2)

GoogleHits(K1) + GoogleHits(K2)-<u>GoogleHits(K1,K2)</u>

## WordNet

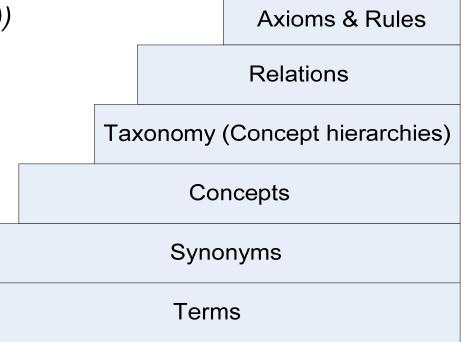
- Idea: Use already created ontologies
- Previously found relations can be used to train other machine learning techniques (e.g. decision trees, association rule learning, neural networks)

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### **Axioms & Rules**

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



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Synonyms

Concepts

**Concept Hierarchies** 

Relations

#### Rules

Conclusions

### Axioms & Rules

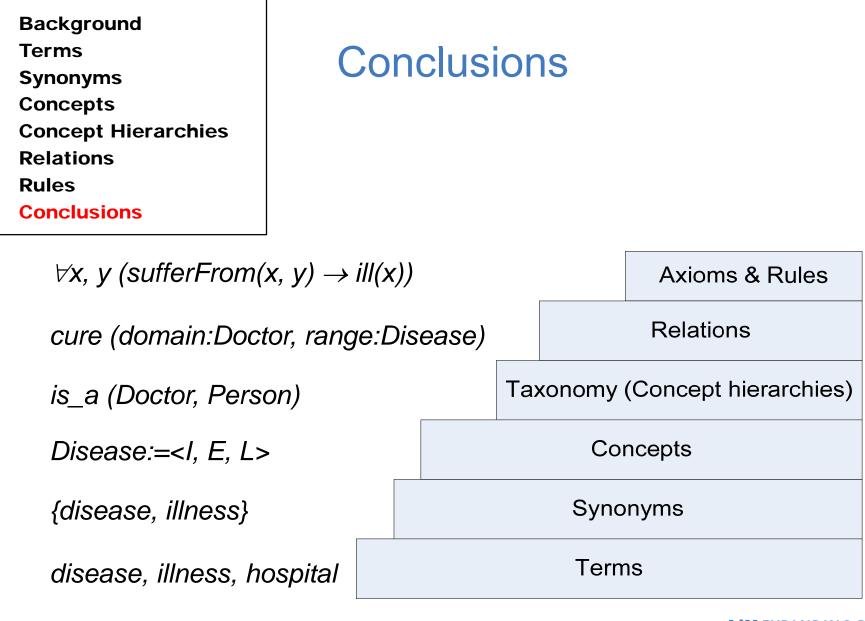
Mostly Lexico-Synthatic Patterns

• Example: LExO

Rule	Natural Language Syntax	OWL Axioms
Disjunction	NP <sub>0</sub> or NP <sub>1</sub>	$X \equiv (\mathrm{NP}_0 \sqcup \mathrm{NP}_1)$
Conjunction	$NP_0$ and $NP_1$	$X \equiv (\mathrm{NP}_0 \sqcap \mathrm{NP}_1)$
Determiner	$Det_0 NP_0$	$X \equiv \mathrm{NP}_0$
Intersective Adjective	Adj <sub>0</sub> NP <sub>0</sub>	$X \equiv (\operatorname{Adj}_0 \sqcap \operatorname{NP}_0)$
Subsective Adjective	Adj <sub>0</sub> NP <sub>0</sub>	$X \sqsubseteq \mathrm{NP}_0$
Privative Adjective	Adj <sub>0</sub> NP <sub>0</sub>	$X \sqsubseteq \neg \operatorname{NP}_0$
Transitive Verb Phrase	$V_0 NP(obj)_0$	$X \equiv \exists V_0.NP_0$
Verb with Prep. Compl.	$V_0 \operatorname{Prep}_0 \operatorname{NP}(pcomp-n)_0$	$X \equiv \exists V_0 \_ Prep_0.NP_0$
Noun with Prep. Compl.	$NP_0 Prep_0 NP(pcomp-n)_1$	$X \equiv (\mathrm{NP}_0 \sqcap \exists \mathrm{Prep}_0.\mathrm{NP}_1)$
Prepositional Phrase	Prep <sub>0</sub> NP <sub>0</sub>	$X \equiv \exists \operatorname{Prep}_0.\operatorname{NP}_0$

Data: Facts that result from measurements or observations. Data  $\equiv$  (Fact  $\sqcap \exists result\_from.(Measurement \sqcup Observation))$ 

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### Conclusions

- Mainly three methods used:
  - Natural language processing (NLP)
  - Statistical methods
  - Using other existing ontology

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# Natural Language Processing

• Positive:

- Easy to find corpus
- High success-rate for certain patterns
- Negative:
  - Hard to model every kind of pattern
  - Ambiguity in natural text

## **Statistical Methods**

• Positive:

- Needed in some parts of the layer cake, like term extraction
- Can give confidence to relations (or synonyms) found by other methods
- Negative:
  - Even if a statistical similarity if found, the relation binding the words together is unknown

# **Use Other Existing Ontology**

Positive:

- Very easy to find relations and definitions
- If a relation or similar is found the probabilityrate of it being correct is very high
- Can be combined in a successful way with other methods
- Negative:
  - Can be hard to find ontologies in specialized areas
  - Words can have multiple meaning

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### References

- [1] Ontology Learning Philipp Cimiano, Alexander M\u00e4dche, Steffen Staab, Johanna V\u00f6lker, 2009.
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- [5] Aquisition of OWL DL Axioms from Lexical Resources – Johanna Völker, Pascal Hitzler and Philipp Cimiano



# Linköping University expanding reality

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2011-06-12



41