# Ontology Learning: Framework, Techniques and a Software Environment

MEANING WS Presentation, San Sebastian



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#### Introduction & Motivation

- Ontology Learning Framework & Techniques
- Text-To-Onto Tool-Environment
- Applications
- Conclusion



# Introduction

- Semantics-driven processing of information has been recently become a hype (= Semantic Web).
- The global vision:
  - Allow machines to read and interpret information that is distributed and heterogeneous, stored in databases, semi-structured documents and free text documents.
  - Allow humans for "semantics-based" access to information.
- This vision is not new, many communities have been working on it, e.g. the
  - Knowledge engineering & Representation Community
  - Natural Language Processing Community
  - Database Community (in the context of Information Integration)



## Introduction

- Lexical and ontological resources are seen as the key for bringing this vision to reality.
- Extracting these resources from data (structured data, semi-structured and free text documents) on which they will be later applied on is promising.
- This presentation will present some work in the field of ontology learning, with specific focus on textual data as input for ontology learning.





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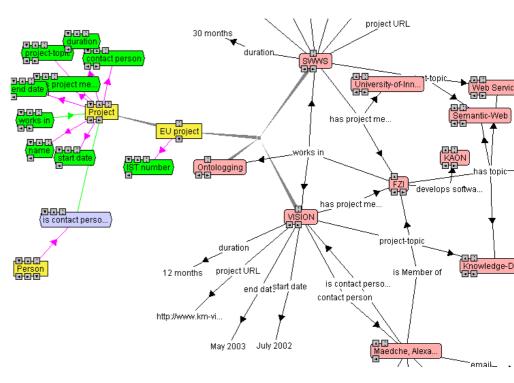


# Ontologies

- Expressive conceptual models, no strict separation between schema and instance.
- OI-model (ontology-instance model)

   elementary information container, contains ontology and instance data:
  - concepts
  - relations
  - instances

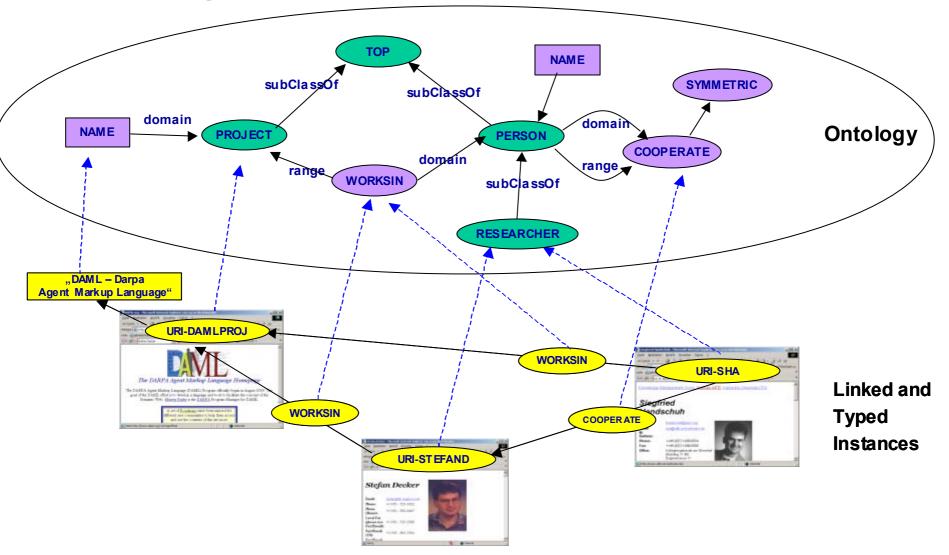




- Extensions of W3C's RDF-Schema, along the same lines of W3C OWL.
- Builds on an expressive hybrid knowledge representation mechanism, inspired by Description Logics paradigm, but executed using deductive database techniques.

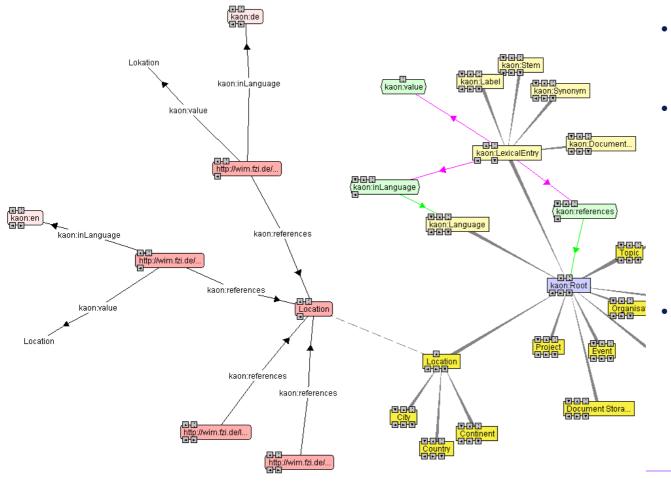


## **Ontologies & Semantic Web**





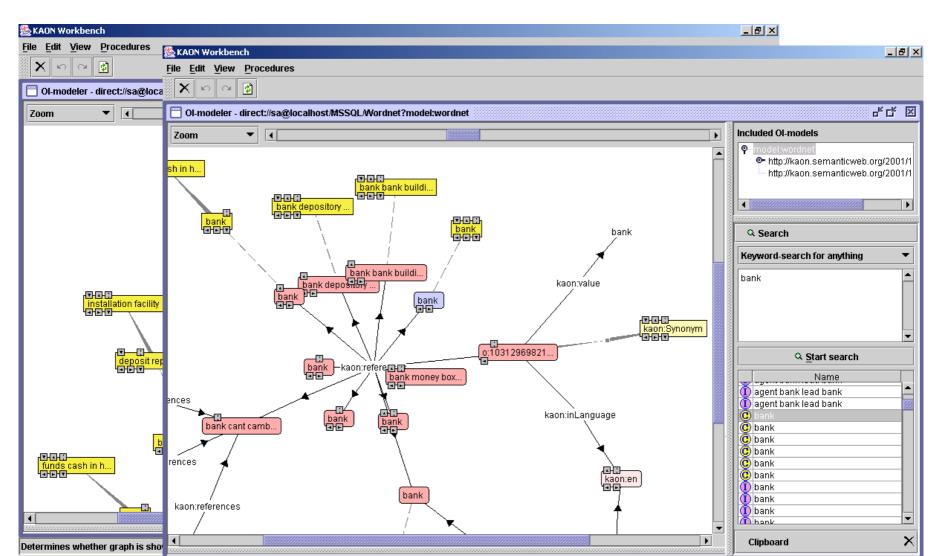
## **Ontology & Natural Language**



- The lexicon is part of the ontology.
  - It is considered as a specific model within the ontology (lexical OI-Model) and is considered as metainformation.
    - It allows to encode multilingual labels, synonyms, etc. etc.



## WordNet seen as an OI-Model



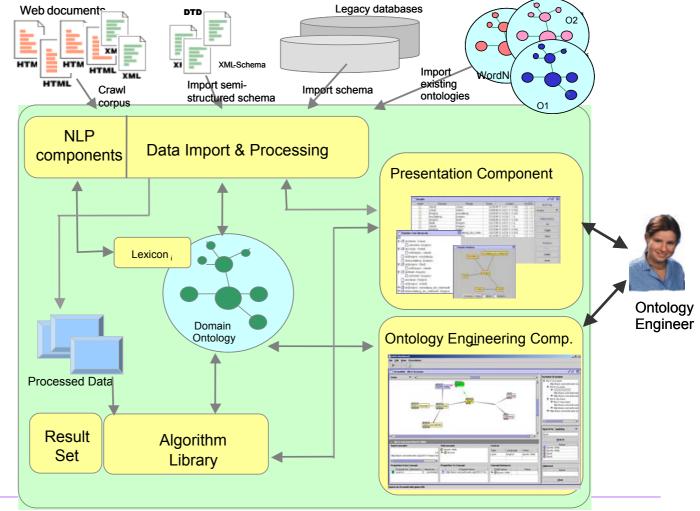


# **Ontology Learning Framework**

 Balanced cooperative modeling architecture

- Incremental and interactive
- Multiple
   resources

 Multiple algorithms





# **Ontology Learning Techniques**

#### **1. Concept Extraction**

- Multi-Word-Term Extraction
- Multi-Word-Term Meaning Extraction

#### 2. Concept Relation Extraction:

- Taxonomy Learning
- Non-taxonomic relation extraction

Beside these two core phases, ontology reuse via "ontology pruning" is provided.



# **Concept Extraction**

#### **Extracting multi-word terms from a given corpus:**

- Term extraction is a basic technology for ontology learning.
- Typically, relevancy measures like tf/idf are used to determine important terms of a corpus.
- Beside the relevancy measures, multi-words term recognition techniques are of importance.

#### **Discovering the meaning of extracted terms:**

- An extracted multi-word term has to be embedded into the ontology, where one typically has several possibilities, e.g. create a new concept, add it as a synonym to an existing concept, etc.
- Within our framework, we provide semi-automatic support for adding an extracted multi-word term to the ontology.
- The approach is based on measuring distributional similarity of the extracted term with existing entities in the ontology.



# **Multi-Word Term Extraction**

- C-value method (\*):
  - Domain-independent method for automatic extraction of multi-word terms, from machine-readable specific language corpora
  - Combines linguistic and statistical information
- Relevancy of terms is determined via the classical tf/idf technique.

(\*) based on: Katerina Frantzi, Sophia Ananiadou, Hideki Mima: *Automatic recognition of multi-word terms: the C-value/NC-value method,* Int J Digit Libr (2000) 3: 115-130



# **Multi-Word Term Meaning Extraction**

For each extracted term and also each concept in given ontology we create following vector:

{term(verb<sub>1</sub>,freq),...,(verb<sub>n</sub>,freq),(noun<sub>1</sub>,freq),...,(noun<sub>t</sub>,freq)}

Where verbs and nouns are considered if they are in the same sentence as the term and in the defined window size.

A distributional distance between each pair of vectors is computed. The smaller the distance is, the more similar terms or concepts (which are described by those vectors) should be.



## **Concept Relation Extraction**

#### **Concept Hierarchy Extraction**

- Lexico-syntactic pattern-based extraction works fine for structured resources like dictionaries.
- Hierarchical clustering did not show a good performance in our experiments, labeling extracted super concepts is a problem.
- Verb-driven approaches seem to work well in some domains (e.g. cooking recipes).

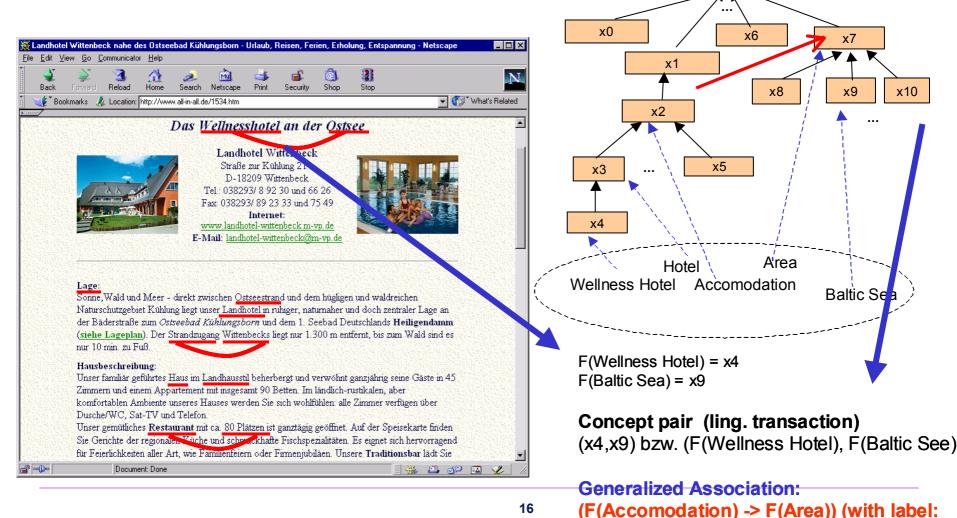
#### **Non-taxonomic Relation Extraction**

- Linguistics and heuristic based association between concepts and the application of an association rule algorithm developed.
- Currently, this is extended with means for automatic relation labeling using a verb-driven approach.



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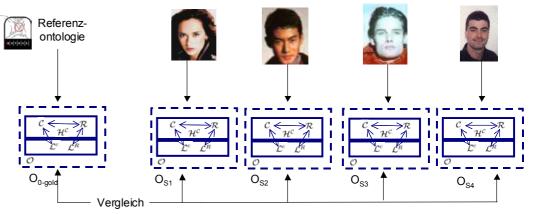
## **Non-Taxonomic Relation Extraction**

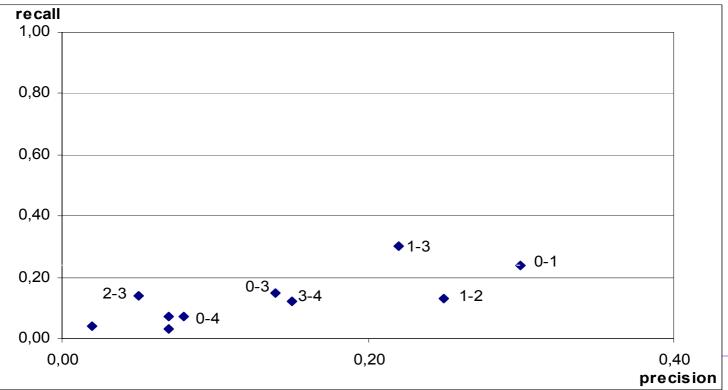


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## **Evaluation**







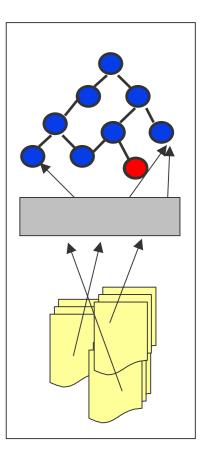
# **Non-Taxonomic Relation - Labeling**

- Problem: relations between concepts extracted via association rules are not labeled.
- Proposed extensions:
  - Verbs are common representants of relations, based on information from POS-tagger
    - 1. Collect verb-concept pairs from corpus
    - 2. Score the verbs (use analogy of TFIDF measure for termdocument occurrences)
    - 3. Let the user select important verbs
  - Find and display verbs, which may be involved in relation between concepts, discovered by association rules, based on statistics of concept-verb occurrences of involved concepts



## Pruning

- Given: An ontology (e.g. WordNet as OI-Model) and a set of domain-specific documents
- Approach: Delete all "unimportant" concepts, means:
  - Based on the lexicon count weighted frequencies and propagate frequencies according to the taxonomy.
  - Define threshold and delete all concepts appearing less than the defined threshold
- A useful method to reuse existing resources (see UN application).





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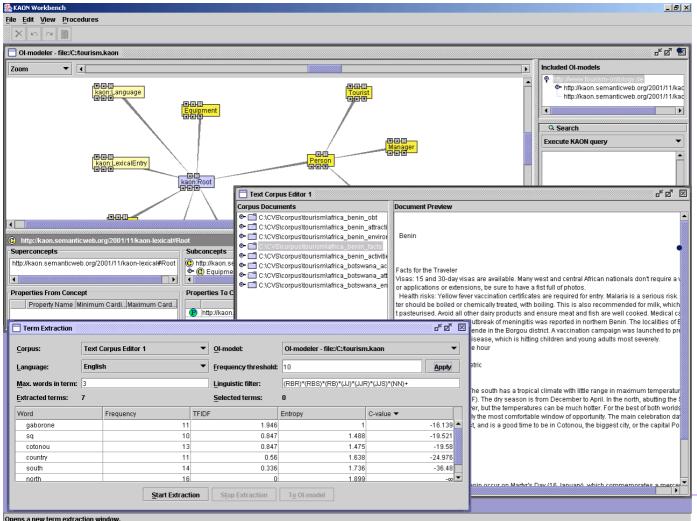
# **KAON & Text-To-Onto**

- KAON stands for Karlsruhe Ontology and Semantic Web Framework.
- Open Source platform for ontology-related tools, including
  - Ontology Modeling tools, including ontology learning
  - Scalable Ontology Server, including API, inference engine and query language.
- Open source under LGPL, available at:

http://kaon.semanticweb.org



### **Text-To-Onto**



Text-To-Onto is tightly integrated into the ontology management architecture KAON.

**Balanced** cooperative modeling approach, means that everything can be done manually, but automatic methods exist.

Opens a new term extraction window



## **Multi-Word Term Extraction**

Corpus: Text C		Corpus Editor 1	•	<u>O</u> I-model:	Ol-modeler - file:/C:/Agabet/	tourism.kaon 🔻
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Max. words in term:	5			Linguistic filter:	(RBR)*(RBS)*(RB)*(JJ)*(JJR)	)*(JJS)*(NN)+
Extracted terms:	971			Selected terms:	0	
Word		Frequency	TFI	DF	Entropy	C-value 🔻
knowledge manag	jeme		499	2.224	0.409	340.335
critical mass			86	3.028	0.468	59.611
prof dr			79	3.883	0.648	54.759
integrated project			87	3.295	0.515	53.372
information societ	y		75	3.117	0.488	51.986
💁 co ordin			70	3.546	0.567	48.52
european researc	h area		43	3.7	0.57	47.24
💁 co oper			65	3.582	0.557	45.055
thematic priority			60	3.988	0.603	41.589
scientific technical	kno		35	5.78	0.883	38.451
sustainable devel	opme		54	4.239	0.684	37.43
knowledge base			52	3.883	0.677	36.044
semantic web			47	4.48	0.69	32.578
thematic area			46	3.413	0.516	31.885
regional knowledg	le		50	6.185	0.899	29.805
membership degr	ee		41	6.878	1	28.419
supply chain			50	4.576	0.763	27.726
european union	_		40	3 743	0.574	27 726

Baseline tool for multi-word term extraction.

•



## **Multi-Word Term Meaning**

				5° 10° 10°
bathroom				•
<ul> <li>distance between term and concepts</li> <li> <ul> <li>0.9354839</li> <li>http://www.tourism-ontology.de#Bed</li> <li>0.95</li> <li>http://www.tourism-ontology.de#Telept</li> <li>0.95238096</li> <li>http://www.tourism-ontology.de#Room</li> <li>0.9661017</li> <li>0.9866667</li> <li>0.9897959</li> <li>0.982268</li> </ul> </li> </ul>	• 🗖 0.8125	ms		
http://www.tourism-ontology.de#Room				
Superconcepts Room (C) Non-Private-Equipment (C) = Private-Equipment (C) =	Subconcepts © Room • © Double-Room • © Single-Room • © Suite	Lexicon Type Label	Language English	Value Room
Properties From Concept Property Na Minimum C Maximum C	Properties To Concept Property Name Property Name	Concept Instances Entity Name Valu		Value
Create subconcept	http://kaon.semanticweb.org/2001/11/k      Create instance     Add to concept	Apply Cha		el recount

Supports the different process of classifying extracted terms into the ontology.



## **Concept Relation Extraction**

									<b>K T F</b>
Relations Extraction									🖋 🖉 🖂
<u>C</u> orpus:	Text Corpus Editor	1	-	Ol-model:		Ol-modeler - file:/C:/	Ol-modeler - file:/C:/tourism.kaon		
Language:	English		-						
	_					_			
	Apply Text Patter	ns				Apply Association	n Rules		
Minimum Support:	0			Minimu	ım Confidence:	0			
Minimum <u>S</u> upport:	0			wiininnu	im <u>connuence</u> :	0			
Apply <u>H</u> ierarchy Reuse	☑ Apply Hierarchy R	euse		Ol-mod	lel for Hierarchy Reuse:	Ol-modeler - file:/C:/	tourism.kaon		•
Premise 🔻	Conclusion	Conclusion Frequen	Support		Confidence	Abs. Freq.	Pattern Names	Property	
Tourist	Region			0.048	0.2	1			
	Museum	4		0.048	0.2	1			333
	Guite	1		0.048	0.2	1			
Tourist F	Festival	2		0.048	0.2	1			
Tourist (	Organisation	2		0.048	0.2	1			
Suite 1	Fourist	5		0.048	1	1			
Restaurant F	Region	6		0.048	0.5	1			
Restaurant H	Hotel	2		0.048	0.5	1			
Region H	Hotel	2		0.048	0.167	1			222
Region 1	Fourist	5		0.048	0.167	1			222
Region F	Festival	2		0.048	0.167	1			222
Region E	3ar	1		0.048	0.167	1			200
	Restaurant	2		0.048	0.167	1			
Region	Country	6		0.048	0.167	1			
	Museum	4		0.048	1	1			
	Fourist	5		0.048	0.5	1			
	Camping	2		0.048	0.5	1			
	Person	1		0.048	0.25	1			
	Dity	2		0.048	0.25	1			
	Country	6		0.048	0.25	1			
	Fourist	5		0.048	0.25	1			
Location	Country	6		0.048	1	1			•
		Start Extraction	Stop Extra	ction	Add as Hierarchy	Add as Property			

Integrated view for extracting relations, including:

- Association
   rules
- Pattern based extraction
- Taxonomy
   reuse



## **Relation explorer**

Relations Extr <u>C</u> orpus:     Language:     Minimum <u>S</u> uppo	Text C Englisi App rt: 0	orpus Editor 1 h wy <u>T</u> ext Patterns		Ol-modeler - file:/C:/sha				1 ;	Provides fo axonomic i associated supporting of extracted	relations verbs, labeling
	ночос 🖂 нрр		Even: P	remise	restivat	Conclusion				•
Premise	Conclusion	Conclusion Fre.	memorial dai		Independence I	Day			relations.	
Travel-Agency	Tourist	7	indian ocean		Country				ciations.	
Event	Festival	6	royal palac		Museum			200		
national galleri	Museum	7	2 Train-Station		City					
memorial dai	Independence	1	Festival		Event City					
art galleri	Museum	7	2 public transport Museum		City	Verb Extractio				
indian ocean	Country	7	town hall		City					
constitution dai	Public Holiday		<sup>D</sup> marino nark		Coast	Corpus:	Text Corpus Editor	1   Ol-model:	Ol-modeler - file:/C:/share/lo	nelvolanet/tourism.kaon
natural history	Museum	7	Theatre		Festival					
christmas dai	Public Holiday	2	5 royal palac		City	Language:	English	<ul> <li><u>Frequency thre</u></li> </ul>	shold: 10	
royal palac	Museum	1	41			Extracted verbs:	· 839	Selected verbs	. 0	
memorial dai	Public Holiday	2		0	25					
national dai cable car	Festival City	8		D. Count	C-Count 🔻	Word	Fr	equency 🔻	TFIDF	Entropy
Train-Station	City	8		P-Count		get		759		
Festival	Event	5	neiu .	3	101	includ		729		
Zoo	City	8		3	34 72	take		709	1	
Balcony	City	8		2	29	make		616		
Motel	City	8		1	97	see		610		
public transport	City	8	2 go	1	25	go		477		
Concert	Fectival	8	21 run	4	25	is in		409		
Г			i held	1	64	is to		392		
	Start Extraction	on Stop Extrac	includ	8	49	come		368		
			get	4	44	find		300	1	
						top		310		
						known		297		
						don		286		
			Property name			visit		267		
						run		258		
						offer		238		
						contain		230		
						is built		223		
								Start Extraction Stop E	Add to OI model	



## **Ontology Pruning/Reuse**

KAON Workbench							
le Edit <u>Vi</u> ew <u>P</u> rocedures							
X 10 04 📓							
Pruner				노다 🗵			
Corpus: Text Corpus Editor 1	•	<u>O</u> I-model:	Ol-modeler - file:/C:/tourism.kaon	▼			
_anguage: English	<b>~</b>	<u>C</u> umulative frequency threshold	: 2	Apply			
Word	Prune	Frequency 🔻	Cumulative	Frequency			
► countri		12	12	A l			
Pregion		9	9				
► region ► museum		8	8				
► tourist		5	5				
P camp		5	5				
P-citi		2	2				
P-hotel		2	2				
Prevent		2	4				
P coast		2	2				
► organis		2	17				
Prestaur		2	2				
P festiv		2	2				
P-locat		1	26				
- person		1	6				
- person ▶ bar		1	1				
P-suit		1	1				
Hotel-Guest		0	0				
archaeological museum		0	0				
SwimmingPool		0	0				
cable car		0	0				
art museum		0	0				
Train-Station		0	0				
christmas dai		0	0				
southern coast		0	0				
music festiv		0	0				
tourist offic		0	0				
Sauna		0	0				
Zoo		0	0				
Double-Room		0	0				
Commercial-Organization		0	7				
national galleri		0	0				
Hair Drier		0	0				
post offic		0	0				
Non-Private-Equipment		0	4				
		~					
	Prepare Pruning L	List Delete Pruned Concept	s Stop Pruner				
ens a new pruner window.							

Allows to user to prune existing ontologies according to a predefined corpus.



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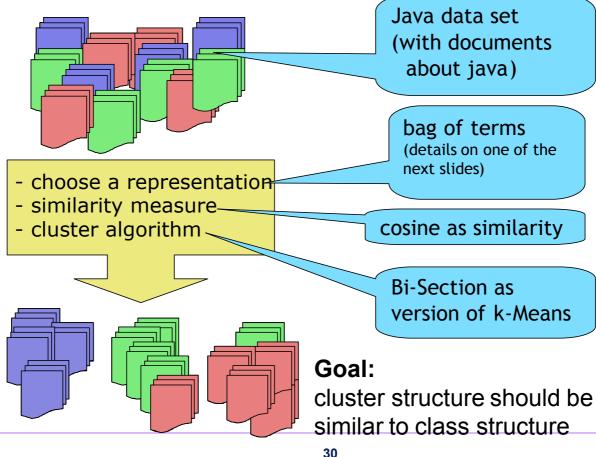


# **Applications of Ontology Learning**

- Text Clustering
  - Exploit ontological background knowledge for document clustering
- Information Extraction
  - Use ontologies as templates for extracting information
- Document Search Application
  - Exploit ontologies for document search



# Text Clustering with Background Knowledge(\*)



(\*) work done by Andreas Hotho, University of Karlsruhe



# **Background Knowledge**

#### **Bag of words model:**

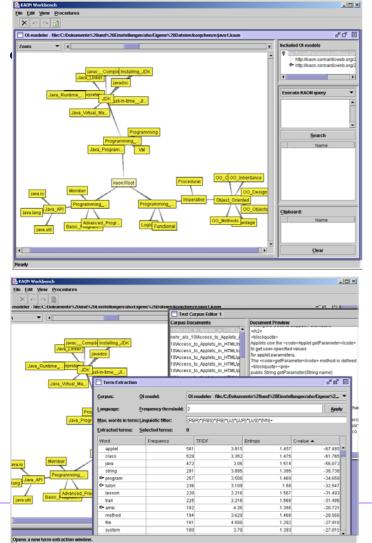
docid	term1	term2	term3	
doc1	0	0	1	
doc2	2	3	1	
doc3	10	0	0	
doc4	2	23	0	

#### **Bag of concept model (term and concept vector):**

docid	term1	term2	term3	 concept1	concept2	concept3	
doc1	0	0	1	0	1	1	
doc2	2	3	1	2	0	1	
doc3	10	0	0	10	0	0	
doc4	2	23	0	2	23	0	



### **Results**



- Without Ontology = Baseline
  - Purity = 62%, Inverse Purity = 61%

#### With handmade Ontology

• Purity = 60%, Inverse Purity = 57%

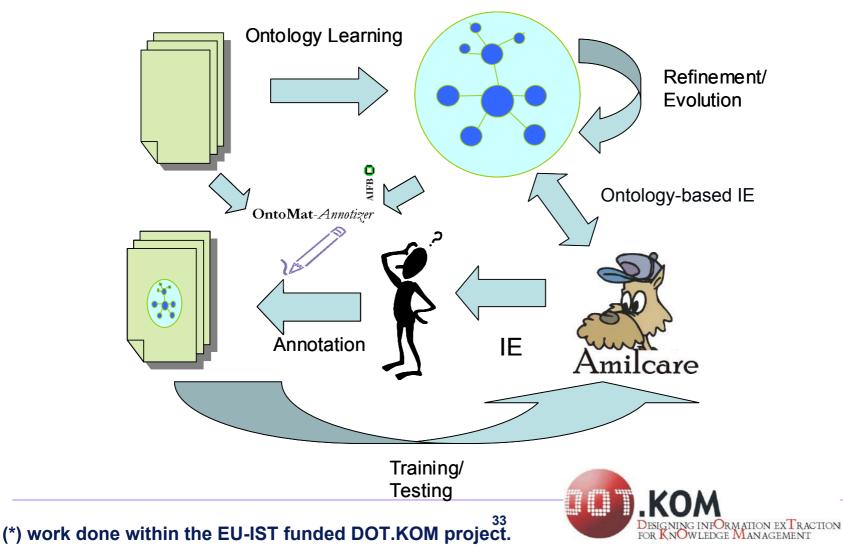
- Ontology improved by Ontology Learning
  - Purity = 67%, Inverse Purity = 64%

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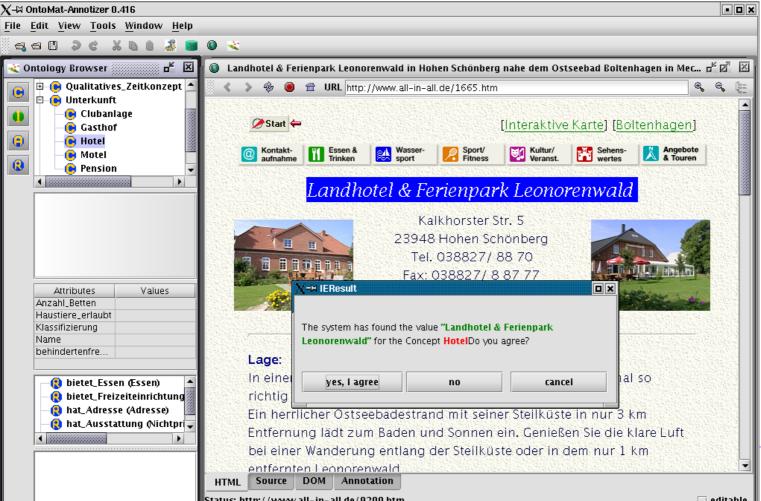


## **Information Extraction (\*)**





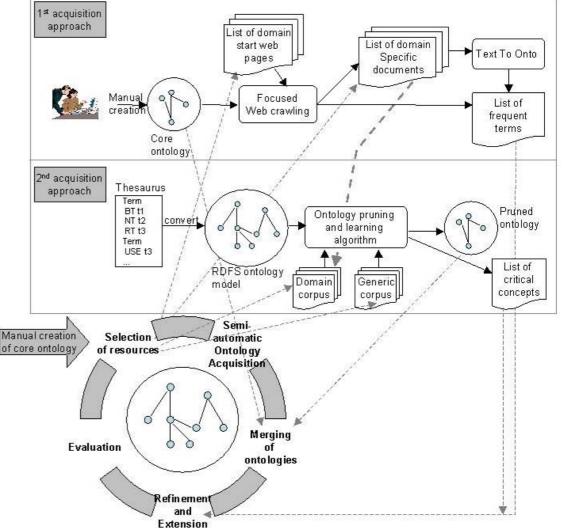
# Ontology-based Information Extraction





## **Document Search Application**

- The Food and Agricultural Organization (FAO) within United Nations is providing means for information dissemination.
- On the basis of the thesaurus AGROVOC a domain specific ontology (food safety animal and plant health) has been generated using pruning.





## **United Nations FAO Application**

Query expansion, ontologybased retrieval of documents

Exploit extracted semantic relations for guiding the user in the search.

The KAON-Portal was created by <u>F.</u>	<u>21</u> and <u>AIFB</u> .		17.4.2002
	Ontology on Food Safety Health	onto joo	
Shortcuts	WTO		
Top Level Concepts			
Language	Related instances		
English f <u>rancais</u> Español 地حينا 中文	• <u>restablish</u> • <u>TBT agreement</u>	• <u>SPS agreement</u>	
Search	Concept Hierarchy		
Search	More general concepts		
Query	Properties		
Click on a button besides an entity to add the concept to the search query SPS agreement	Properties to this concept    require  establish  refer to  derived from  include  follow  sustain	<ul> <li><u>followed by</u></li> <li><u>cause by</u></li> <li><u>constitute</u></li> <li><u>compose</u></li> <li><u>interact with</u></li> <li><u>part of</u></li> <li><u>protected by</u></li> </ul>	
Query Reset	<ul> <li><u>comprise</u></li> <li><u>involve</u></li> <li>Properties from this concept</li> <li>require</li> </ul>	<ul> <li>influence</li> <li>followed by</li> </ul>	
	<ul> <li>refer to</li> <li>derived from</li> </ul>	<ul> <li><u>cause by</u></li> <li><u>constitute</u></li> <li><u>compose</u></li> </ul>	



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## Conclusion

- Ontologies are central for realizing the vision of semantics-based processing of information.
- Ontology learning is a promising step towards approaching the knowledge acquisition bottleneck.
- In this presentation a balanced cooperative approach has been presented.



## **Some Comments for MEANING**

- Knowledge representation issue: How far do you go with semantics?
- Standards issue: The MEANING repository should be somehow aligned with existing standards to make the resources more widely usable.
- Tool issue: To make algorithms usable they have to be integrated into a tool environment and a common framework.



# Thank you for your attention!



#### A. Maedche

Forschungszentrum Informatik an der Universität Karlsruhe

**Research Group WIM** 

http://www.fzi.de/wim



Results		
filter	Corpus1	Corpus2
	"Human Language Technology"	"Eol-Knowledge- Technologies"
[(NNS)(NN)]+	88% (*)	80%
	(1230,233,27) (**)	(1079,202,40)
	86%	76%
(RB)*(JJ)*[(NN)(NNS)]+		
	(1362,362,47)	(1243,361,85)
[(RB)(JJ)(NN)]*(IN)?	64%	64%
[(RB)(JJ)(NN)]*		
[(NN)(NNS)]	(1511,511,181)	(1362,478,171)

(\*) Of precision

(\*\*) (number of all extracted terms, number of multiword terms, number of incorectly extracted multiword terms)



## Preprocessing

#### build a bag of words model

docid	term1	term2	term3	
doc1	0	0	1	
doc2	2	3	1	
doc3	10	0	0	
doc4	2	23	0	

extract word counts (term frequencies) remove stopwords pruning: drop words with less than 30 occurrences weighting of document vectors with tfidf

(term frequency - inverted document frequency)

$$tfidf (d,t) = tf (d,t) * \log$$

 $\begin{array}{c|c} |D| & \text{no. of documents } d \\ df(t) & \text{no. of documents } d & \text{which} \\ \hline & \text{contain term } t \end{array}$