| Ontology Learning (from text!) |
| :---: |
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## Outline

- Definitions and description
- Machine Learning and Natural Language Processing for Ontology Learning
- Ontology Building Applications


## Part I

Definitions and description

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What about: Thesauri - Semantic lexicons Semantic networks?

- Thesauri: standard set of relations between words or terms
- Semantic lexicons: lexical semantic relations between words or more complex lexical items
- Semantic networks: broader set of relations between objects
$>$ Differ in the type of objects and relations

Thesaurus: example

- Roget: thesaurus of English words and phrases - groups words in synonym categories or concepts
- Sample categorization for the concept "Feeling":

AFFECTIONS IN GENERAL
Affections
Feeling
warmth, glow, unction, vehemence;
fervor, fervency;
heartiness, cordiality;
earnestness, eagerness;
empressment, gush, ardor, zeal, passion...

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## Thesaurus: example

- MeSH (Medical Subject Headings) - provides for each term term variants that refer to the same concept
- MH= gene library bank, gene DNA libraries gene libraries libraries, gene library, gene
banks, gene gene banks libraries, DNA library, DNA


## Semantic network: example

- UMLS: Unified Medical Language System
- Metathesaurus: groups term variants that correspond to the same concept


## HIV

HTLV-III
Human Immunodeficiency Virus

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## Semantic lexicon: example

- WordNet: set of semantic classes (synsets)
- \{board, plank\}, \{board, committee\}
- tree
woody_plant ligneous_plant vascular_plant tracheophyte plant flora plant_life life_form organism_being living_thing entity something
- tree tree diagram
... abstraction
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## Semantic Network: example

- UMLS: Unified Medical Language System
- Semantic Network: organises all concepts of the metathesaurus into semantic types and relations (2 semantic types can be linked by several relations):
pharmacologic substance affects pharmacologic substance causes
pathologic function pathologic function pharmacologic substance prevents pathologic function

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## Semantic Network: example

- CYC: contains common sense knowledge: trees are outdoors people who died stop buying things ...
\#\$mother :
(\#\$mother ANIM FEM) isa: \#\$FamilyRelationSlot \#\$BinaryPredicate

So, what's an ontology?

- Ontologies are defined as a formal specification of a shared conceptualization Borst, 97
- An ontology is a formal theory that constrains the possible conceptualizations of the world

Guarino, 98

What an ontology is (maybe)

- Community agreement
- Relations between terms
- Pragmatic information
- Common sense knowledge
- Meaning of concepts vs. words: explore language more deeply

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Why ontologies?
$>$ Information retrieval
$>$ Word Sense Disambiguation
> Automatic Translation
$>$ Topic detection
$>$ Text summarization
$>$ Indexing
$>$ Question answering
$>$ Query improvement
$>$ Enhance Text Mining
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What can be used?

- Texts
- Existing ontologies or core ontologies
- Dictionaries, encyclopediae
- Experts
- Machine Learning and Natural Language Processing tools

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What kind of ontology?

- More or less domain specific
- Supervised/unsupervised
- Informal/formal
- For what purpose?
$\Rightarrow$ determines the granularity, the material, the resources...

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## Supervised/unsupervised

- One extreme: from scratch
- Other extreme: manual building
- Using a core ontology, structured data...
- Different strategies
- Different tools
- Advantages and inconveniences

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## Operations on ontologies

- Extraction: building of an ontology
- Pruning: removing what is out of focus; danger: keep the coherence
- Refinement: fine tuning the target (e.g. considering user requirements)
- Merging: mixing of 2 or more similar or overlapping source ontologies
- Alignment: establishing links between 2 source ontologies to allow them to share information
- Evaluation: task-based, necessity of a benchmark!
- ...

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## Components

- Classes of words and concepts
- Relations between concepts
- Axioms defining different kind of constraints
- Instances that can represent specific elements

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## Relations

- Meronymic

From group to members
team $\rightarrow$ goalkeeper copilot $\rightarrow$ crew
From parts to wholes book $\rightarrow$ cover wheels $\rightarrow$ car
From events to subevents snore $\rightarrow$ sleep

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## Relations

- Thematic roles
agent: causer of an event
"the burglar" broke the window
experiencer (of an event)
"the woman" suffers injuries from the car accident
force: non voluntary causer of an event
"the earthquake" destroyed several buildings
theme: participant most directly affected by an event
the burglar broke "the door"


## Relations

- Thematic roles
instrument (used in an event)
I've eventually forced the lock "with a screwdriver'
source: origin of an object of a transfer event he's coming "from Norway"
beneficiary (of an event)
she's knitting socks "for her grandchildren"


## Relations

- Thematic roles can be augmented by the notion of semantic restrictions
- Selectional restrictions: semantic constraint imposed by a lexeme on the concepts that can fill the various arguments roles associated with it
- "I wanna eat some place that's close to the cinema."
"I wanna eat some spicy food."
- "Which airlines serve Denver?"
"Which airlines serve vegetarian meals?"

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TM and NLP for ontology extraction from text

- lexical information extraction
- syntactic analysis
- semantic information extraction

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## Collocations

- A collocation is an expression consisting of two or more words that correspond to some conventional way of saying things
- Technique: count occurrences, rely on frequencies (pb with sparse data)


## Lexical acquisition

collocations
n-grams

Text Mining and Natural Language Processing for ontology extraction from text

| Lexical acquisition |
| :---: |
| collocations |
| n -grams |
|  |
|  |
| Apil28, os |

## Mutual information <br> $\mathbf{I}(\mathbf{x}, \mathbf{y})=\log \left[\mathbf{f}(\mathbf{x}, \mathbf{y}) /\left(\mathbf{f}(\mathbf{x})^{*} \mathbf{f}(\mathbf{y})\right]\right.$

- extract multiwords units
- group similar collocates or words to identify different meanings of a word
- bank river
- bank investment

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## High similarity?

- Strong $\cong$ powerful
- I(strong, tea) >> I(powerful, tea)
- I(strong, car) << I(powerful, car)


## So...

- Mutual information shows some dissimilarity between "strong" and "powerful", but how can we measure that dissimilarity? strong tea vs. ${ }^{*}$ powerful tea


## $\rightarrow$ T-test

| Mutual information |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $\mathrm{I}(\mathrm{x}, \mathrm{y})$ fxy fx fy x <br> 10,47 7 7809 28 strong <br> northerly     <br> 9,76 23 7809 151 strong <br> showings     <br> 9,30 7 7809 63 strong <br> believer     <br> 9,04 10 7809 108 strong <br> currents     <br> 8,66 7 1984 388 powerful <br> legacy     <br> 8,58 7 1984 410 powerful <br> tool     <br> 8,35 8 1984 548 powerful <br> storms     <br> 8,32 31 1984 2169 powerful <br> minority     |  |  |  |  |  |
| $\mathbf{I}(\mathbf{x , y} \mathbf{y})=\log [\mathbf{f}(\mathbf{x}, \mathbf{y}) /(\mathbf{f}(\mathbf{x}) * \mathbf{f}(\mathbf{y})]$ |  |  |  |  |  |
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## Statistical inference: n -grams

- Consists of taking some data and making some inferences about their distribution: counting words in corpora
- Example: the n-grams mode
- The assumption that the probability of a word depends only on the previous word is a Markov assumption.
- Markov models are the class of probabilistic models that assume that we can predict the probability of some future unit without looking too far into the past

A bigram is a first-order Markov model
A trigram is a second-order Markov model
...

## Problems

- Wordform / lemma
- Capitalized tokens
- Sparse data
- Deal with huge collections of texts

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TM and NLP for ontology extraction from text

- lexical information
- syntactic analysis
- semantic information extraction

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## Example: Shallow Parser

- Tokenizer output

The patients followed a ‘ healthy ‘ diet and $20 \%$ took a high level of physical exercise.

- Tagger output

The/DT patients/NNS followed/VBD a/DT
' $/$ " healthy/JJ ‘/" diet/NN and/CC 20/CD
\%/NN took/VBD a/DT high/JJ level/NN of/IN physical/JJ exercise/NN ./.

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## Example

- "eat" is followed by: on, some, lunch, dinner, at, Indian, today, Thai, breakfast, in, Chinese, Mexican, tomorrow, dessert, British
- "restaurant" is preceded by: Chinese, Mexican, French, Thai, Indian, open, the, a
- Intersection: Chinese, Mexican,Thai, Indian


## Technique: parsing

- Part Of Speech tagging
- Chunking
- Specific relations
- Unsupervised?
- Shallow?
- Efficiency? (resources, processing time)

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## Chunker output

[NP The/DT patients/NNS NP]
[VP followed/VBD VP]
[NP a/DT ‘/" healthy/JJ ‘/" diet/NN NP]
and/CC [NP 20/CD \%/NN NP]
[VP took/VBD VP]
[NP a/DT high/JJ level/NN NP]
\{PNP [Prep of/IN Prep] [NP physical/JJ exercise/NN NP] PNP\} ./.

TM and NLP for ontology extraction from text

- lexical information
- syntactic analysis
- semantic information extraction

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## Selectional preferences or restrictions

- The syntactic structure of an expression provides relevant information about the semantic content of that expression
- Most verbs prefer arguments of a particular type
disease prevented by immunization infection prevented by vaccination hypothermia prevented by warm clothes

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## Statistical measures

- Frequency measure:
$\mathrm{F}(\mathrm{c}, \mathrm{v})=\mathrm{f}(\mathrm{c}, \mathrm{v}) / \mathrm{f}(\mathrm{c})+\mathrm{f}(\mathrm{v})$
- Standard Probability measure:
$\mathrm{P}(\mathrm{c} \mid \mathrm{v})=\mathrm{f}(\mathrm{c}, \mathrm{v}) / \mathrm{f}(\mathrm{v})$
- Hindle Mutual Information measure:
$\mathrm{H}(\mathrm{c}, \mathrm{v})=\log \{\mathrm{P}(\mathrm{c}, \mathrm{v}) /[\mathrm{P}(\mathrm{v}) * \mathrm{P}(\mathrm{c})]\}$
focus on the verb-object cooccurrence
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## Techniques

- Selectional restrictions
- Semantic similarity
- Clustering
- Pattern matching

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## Semantic similarity

- Automatically acquiring a relative measure of how similar a new word is to known words (or how dissimilar) is much easier than determining its meaning.
- Vector space measures: vector similarity
- Add probabilistic measures: refinement

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More statistical measures

- Resnik: $\mathrm{R}(\mathrm{c}, \mathrm{v})=\mathrm{P}(\mathrm{c} \mid \mathrm{v}) * \mathrm{~S}_{\mathrm{R}}(\mathrm{v})$
with $\quad \mathrm{S}_{\mathrm{R}}(\mathrm{v})=\sum\{\mathrm{P}(\mathrm{c} \mid \mathrm{v}) * \log [\mathrm{P}(\mathrm{c} \mid \mathrm{v}) / \mathrm{P}(\mathrm{c})]\}$
selectional preference strength
focus on the verb
- Jaccard: $\mathrm{J}(\mathrm{c}, \mathrm{v})=\log 2 \mathrm{P}(\mathrm{c} \mid \mathrm{v}) * \log 2 \mathrm{f}(\mathrm{c}) / \# \mathrm{c}$ ctx
with \#c ctx = number of contexts of appearance for the compound c
focus on the nominal string
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Semantic dissimilarity: Contrastive corpus

- Used to discard
- general terms
- unfocused domain terms
- Wall Street Journal vs. Medical corpus

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## Clustering

- Unsupervised method that consists of partitioning a set of objects into groups or clusters, depending on the similarity between those objects
- Clustering is a way of learning by generalizing.


## Clustering

- Generalizing: assumption that an environment that is correct for one member of the cluster is also correct for the other members of the cluster
- Example: preposition to use with "Friday"?
1.Existence of a cluster " Monday, Sunday, Friday"

2. Presence of the expression "on Monday"
3. Choice of the preposition "on" for
"Friday"

## Hierarchical

- Bottom-up (agglomerative): starting with each objet as a cluster and grouping the most similar ones
- Top-down (divisive clustering): all objects are put in one cluster and the cluster is divided into smaller clusters (use of dissimilarity measures)


## Types of clustering

- Hierarchical: each node stands for a subclass of its mother's node; the leaves of the tree are the single objects of the clustered sets
- Non hierarchical or flat: relations between clusters are often undetermined
- Hard assignment: each object is assigned to one and only one cluster
- Soft assignment allows degrees of membership and membership in multiple clusters (uncertainty)
- Disjunctive clustering: "true" multiple assignment
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## Example bottom-up

- Three of the 10000 clusters found by Brown et al, (1992), using a bigram model and a clustering algorithm that decreases perplexity:
- plan, letter, request, memo, case, question, charge, statement, draft
- day, year, week, month, quarter, half
- evaluation, assessment, analysis, understanding, opinion, conversation, discussion


## Non hierarchical

- Often starts with a partition based on randomly selected seeds (one seed per cluster) and then refine this initial partition
- Several passes are often necessary. When to stop? You need to have a measure of goodness and you go on as long as this measure is increasing enough

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Pattern matching / Association rules

Pattern matching consists of finding patterns in texts that induce a relation between words, and generalizing these patterns to build relations between concepts

## Example

- Finding associations that occur between items, e.g. supermarket products, in a set of transactions, e.g. customers' purchases.
- Generalization:
"snacks are purchased with drinks" is a generalization of
"chips are purchased with bier" or "peanuts are purchased with soda"


## Examples

- AutoClass (Minimum Description Length): the measure of goodness captures both how well the objects fit into the clusters and how many clusters there are. A high number of clusters is penalized.
- EM alorithm
- K-means
- ...

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## Srikant and Agrawal algorithm

This algorithm computes association rules $\mathrm{Xk} \Rightarrow \mathrm{Yk}$, such that measures for support and confidence exceed user-defined thresholds.
Support of a rule $\mathrm{Xk} \Rightarrow \mathrm{Yk}$ is the percentage of transactions that contain Xk U Yk as a subset
Confidence is defined as the percentage of transactions that Yk is seen when Xk appears in a transaction.
Apili 2, os

## References

- Manning and Schutze, "Foundations of Statistical natural Language Processing"
- Mitchell, "Machine Learning"
- Jurafsky and Martin, "Speech and Language Processing"
- Church et al., "Using Statistics in Lexical Analysis". In Lexical Acquisition (ed. Uri Zernik)

Part III: Ontology Building Systems

1. TextToOnto (AIFB, Karlsruhe)
2. CORPORUM-OntoBuilder (Ontoknowledge project)
3. OntoLearn
4. Mumis (European project)
5. OntoBasis (CNTS)

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## 1. Text To Onto

This system supports semi-automatic creation of ontologies by applying text mining algorithms.

- Generic core ontology used as a top level structure
- Domain specific concepts acquired and classified from a dictionary
- Shallow text processing
- Term frequencies retrieved from texts
- Pattern matching
- Help from an expert to remove concepts unspecific to the domain

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## Learning and discovering algorithms

- The term extraction algorithm extracts from texts a set of terms that can potentially be included in the ontology as concepts.
- The rules extraction algorithm extracts potential
taxonomic and non-taxonomic relationships between existing ontology concepts. Two distinct algorithms: the regular expression-based pattern matching algorithm mines a concept taxonomy from a dictionary the learning algorithm for discovering generalized association rules analyses the text for non-taxonomic relations
- The ontology pruning algorithm extracts from a set of texts the set of concepts that may potentially be removed from the ontology.


## Learning algorithm

- Text corpus for tourist information (in German), that describes locations, accomodations, administrative information...
- Example: Alle Zimmer sind mit TV, Telefon, Modem und Minibar ausgestattet. (All rooms have TV, telephone, modem and minibar.)
- Dependency relations output for that sentence: Zimmer - TV (room - television)

| Example |  |  |
| :---: | :---: | :---: |
| - Tourist information text corpus <br> - Concepts pairs derived from the text: <br> area - hotel <br> hairdresser - hotel <br> balcony - access <br> room - television | - Domain <br> furnishing accomodat hotel |  |
| - Discovered relations | Support | Confidence |
| (area, accomodation) |  | $\begin{array}{r}0.04 \\ 0.03 \\ \hline\end{array}$ |
| (area, hotel) |  | 0.03 |
| (room, furnishing) | 0.29 | 0.02 |
| (room, tetevision) | 0.34 | 0.05 |
| (accomodation, address) (restaurant, accomodation) | 0.33 | 0.02 |
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## Ontology: example

-<rdfs:Class rdf:about="test:cat">
<rdfs:subClassOf rdf:resource="test:animal" />
</rdfs:Class>
= <rdfs:Class rdf:about="test:persian_cat">
<rdfs:subClassOf rdf:resource="test:cat" />
</rdfs:Class>
<!-- properties of cars and cats -->
=<rdf:Property rdf:about="test:color">
<rdfs:domain rdf:resource="test:car" / >
<rdfs:domain rdf:resource="test:cat" />
</rdf:Property>
<!-- properties between cars and cats -->
=<rdf:Property rdf:about="test:runs_over">
<rdfs:domain rdf:resource="test:car" />
<rdfs:domain rdf:resource="test:car" $/>$
<rdfs:range rdf:resource="test:cat" />
<rdfs:range rdf:
</rdf:Property>
http://kaon.semanticweb.org/frontpage
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## 2. Ontoknowledge

Content-driven Knowledge-Management through Evolving Ontologies

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## OntoBuilder

- Ontowrapper: structured documents (names, telephone numbers...)
- OntoExtract: unstructured documents - provide initial ontologies through semantic analysis of the content of web pages
- refine existing ontologies (key words, clustering...)

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| OntoWrapper |
| :---: |
| • Deals with data in "regular" pages |
| • Uses personal "extraction rules" |
| • Outputs instantiated schemata |
|  |
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## OntoExtract

Taking a single text or document as input, OntoExtract retrieves a document specific light-weight ontology from it.

Ontologies extracted by OntoExtract are basically taxonomies that represent classes, subclasses and instances.

## OntoExtract: Why?

- concept extraction
- relations extraction
- semantic discourse representation
- ontology generation
- part of document annotations
- document retrieval
- document summarising
- ...

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## OntoExtract

## - learning initial ontologies

-> propose networked structure

- refining ontologies
$->$ add concepts to existing onto's
-> add relations "across" boundaries

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## OntoExtract

- Classes, described in the text which is analysed
- Subclasses, classes can also be defined as subclass of other classes if evidence is found that a class is indeed a subclass of another class.
- Facts/instances: Class definitions do not contain properties. As properties of classes are found, they will be defined as properties of an instance of that particular class.

The representation is based on relations between classes based on semantic information extracted. April 28, 05

OntoExtract: How?

Extraction Technology based on

- tokeniser
- morphologic analysis
- lexical analysis
- syntactic/semantic analysis
- concept generation
- relationships

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Example
<rdfs:Class rdf:ID="news_service">
<rdfs:subClassOf rdf:resource="\#service"/>
</rdfs:Class>
<news_service rdf:ID="news_service_001">
<hasSomeProperty>financial</hasSomePropert
y>
</news_service>
April2s,0s


## Query example

http://sesame.aidministrator.nl/publications/rql-tutorial.html\#N366 http://sesame.aidministrator.nl/sesame/actionFrameset.jsp?repository=museum select $\mathrm{X}, \$ \mathrm{X}, \mathrm{Y}$ from $\{\mathrm{X}: \$ \mathrm{X}\}$ cult:paints $\{\mathrm{Y}\}$ using namespace cult =
http://www.icom.com/schema.rdf\#
select $\mathrm{X}, \mathrm{Z}, \mathrm{Y}$ from $\{\mathrm{X}\}$ rdf:type $\{\mathrm{Z}\},\{\mathrm{X}\}$ cult:paints $\{\mathrm{Y}\}$ using namespace $\mathrm{rdf}=$ http://www.w3.org/1999/02/22-rdf-syntax-ns\# , cult =
http://www.icom.com/schema.rdf\#
select $\mathrm{X}, \mathrm{Y}$ from $\{\mathrm{X}$ : cult:Cubist $\}$ cult:paints $\{\mathrm{Y}\}$ using namespace cult $=$ http://www.icom.com/schema.rdf\#
select $X, S X, Y$ from $\{X: S X\}$ cult:last name $\{Y\}$ where $(\$ X<=$ cult:Painter and Ylike "P*) or ( $\$ \mathrm{X}<=$ cult.Sculptor and not $Y$ like "B*") using namespace cult $=$ http://www.icom.com/schema.rdf
select PAINTER, PAINTING, TECH from \{PAINTER\} cult:pain
\{PAINTING\} . cult:technique $\{$ TECH $\}$ using namespace cult $=$
http://www.icom.com/schema.rdf\#

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Query example
select PAINTER, PAINTING, TECH from \{PAINTER\} cult:paint \{PAINTING\}. cult:technique $\{$ TECH $\}$ using namespace cult $=$
http://www.icom.com/schema.rdf\#
Query results: PAINTER PAINTING TECH
http://www.european-history.com/picasso.html http://www.european$\frac{\text { http://www.european-history.com/picasso.html }}{\text { history.com/ipg } / \text { guernica003.jpg "oil on canvas" }(a) \text { en }}$
http://www.european-history.com/picasso.html http://www.museum.es/woman.gti "oil on canvas"@en
http://www.artchive.com/rembrandt/artist at his easel.jpg "oil on canvas"@en http://www.european- history.com/rembrandt htm
http://www.artchive.com/rembrandt/abraham.jpg "oil on canvas"@en
http://www.european-history.com/goya.htm
http://192.41.13.240/artchive/graphics/saturn zoom1.jpg "wall painting
(oil)"@en $\quad 5$ results found in 323 ms .
http://www.ontoknowledge.org
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OntoLearn

An infrastructure for automated ontology learning from domain text.

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## Semantic interpretation

- Identifying the right senses (concepts) for complex domain term components and the semantic relations between them.
- use of WordNet and SemCor
- creation of Semantic Nets
- use of Machine Learned Rule Base
- Domain concept forest

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## 4. MUMIS

Goal: to develop basic technology for automatic indexing of multimedia programme material

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## MUMIS

- Domain: soccer
- Developement of an ontology and a multilanguage lexica for this domain
- Query: "give me all goals Uwe Seeler shot by head during the last 5 minutes of a game" (formal query interface)
- Answer: a selection of events represented by keyframes

| 4. MUMIS |
| :---: |
| Goal: to develop basic technology for <br> automatic indexing of multimedia <br> programme material |
|  |
| April2 8,05 |

## Ontology Integration

- from a core domain ontology or from WordNet
- Applied to multiword term translation
http://www.ontolearn.de


## MUMIS

- Use data from different media sources (documents, radio and television programmes) to build a specialised set of lexica and an ontology for the selected domain (soccer).
- Access to textual and especially acoustic material in the three languages English, Dutch, and German

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## Information Extraction

- Natural Language Processing (Information Extraction)

Analyse all available textual documents (newspapers, speech transcripts, tickers, formal texts ...), identify and extract interesting entities, relations and events

- The relevant information is typically represented in form of predefined "templates", which are filled by means of Natural Language analysis
- IE combines here pattern matching, shallow NLP and domain knowledge
- Cross-document co-reference resolution

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## IE subtasks

- Named Entity task (NE): Mark into the text each string that represents, a person, organization, or location name, or a date or time, or a currency or percentage figure.
- Template Element task (TE): Extract basic information related to organization, person, and artifact entities, drawing evidence from everywhere in the text.

Terms as descriptors and terms for NE task

Team: Titelverteidiger Brasilien, den respektlosen Außenseiter Schottland Trainer: Schottlands Trainer Brown, Kapitän Hendry seinen Keeper Leighton
Time: in der 73. Minute, nach gerade einmal 3:50 Minuten, von Roberto Carlos (16.), nach einer knappen halben Stunde,

## IE subtasks

- Template Relation task (TR): Extract relational information on employee_of, manufacture_of, location_of relations etc. (TR expresses domain-independent relationships).
Opponents: Brasilien besiegt Schottland,
feierte der Top-Favorit
Trainer_of: Schottlands Trainer Brown

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## IE subtasks

- Scenario Template task (ST): Extract prespecified event information and relate the event information to particular organization, person, or artifact entities (ST identifies domain and task specific entities and relations).
Foul: als er den durchlaufenden Gallacher im Strafraum allzu energisch am Trikot zog Substitution: und mußte in der 59. Minute für Crespo Platz machen...


## IE subtasks

- Co-reference task (CO): Capture information on co-referring expressions, i.e. all mentions of a given entity, including those marked in NE and TE.


## On-line task

- Searching and Displaying
- Search for interesting events with formal queries

Give me all goals from Overmars shot with his head in 1. Half.
Event=Goal; Player=Overmars; Time $<=45$; Previous-Event=Headball

- Indicate hits by thumbnails \& let user select scene
- Play scene via the Internet \& allow scrolling etc
- User Guidance (Lexica and Ontology)

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## 5. OntoBasis

Elaboration and adaptation of semantic knowledge extraction tools for the building of specific domain ontology


| Unsupervised learning |  |
| :---: | :---: |
| [NP1Subject The/DT Sarsen/NNS Circle/NNP NP1Subject] [VP1 is/VBZ VP1]... | $\begin{array}{cc} \text { NNP } & \text { raw text } \\ \downarrow & \downarrow \text { shallow parser } \\ \end{array}$ |
| mutation in gene | $\underset{\text { matching }}{\downarrow \text { pattern }}$ |
| catalytic_subunit of | relations |
| DNA_polymerase | $\downarrow$ statistics |
|  | relevant relations |
|  | $\downarrow$ evaluation |
|  | nitiation of an ontology |
| Appil 2 , 05 | 102 |

## Material

- Stonehenge corpus, 4 K words, rewritten
- Extraction of semantic relations using pattern matching and statistical measures
- Focus on "part of" and spatial relations, dimensions, positions...


## Syntactic analysis

The Sarsen Circle is about 108 feet in diameter
The/DT Sarsen/NNS Circle/NNP is/VBZ about/IN
108/DT feet/NNS in/IN diameter/NN ./.
[NP The/DT Sarsen/NNS Circle/NNP NP]
[VP is/VBZVP]
[NP about/IN 108/DT feet/NNS NP] [PP in/IN PP] [NP diameter/NN NP] ./.
[NP1Subject The/DT Sarsen/NNS Circle/NNP NP1Subject] [VP1 is/VBZ VP1]
[NP about/IN 108/DT feet/NNS NP]

$$
\{\mathbf{P N P}[\mathbf{P P} \text { in/IN PP }][\mathrm{NP} \text { diameter/NN NP] } \mathbf{P N P}\} . /
$$

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## Selection

- Nominal Strings filtering using a statistical measure: the measure is high when the prepositional structure is coherent
- We select the N most relevant structures

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$$
\frac{\frac{\text { \#NS1-P-NS2 }}{\text { Min(\#NS1,\#NS2) }}}{\frac{\text { \#NS1-P }}{\text { \#NS1 }}+\frac{\text { \#P-NS2 }}{\text { \#NS2 }}}
$$

## Stonehenge corpus

- Description of the megalithic ruin

The trilithons are ten upright stones
The Sarsen heel stone is 16 feet high.
The bluestones are arranged into a horseshoe shape inside the trilithon horseshoe.

## Pattern matching

- Selection of the syntactic structures

Nominal String - Preposition - Nominal String Ns-Prep-Ns
[a Ns is a string of adjectives and nouns, ending up with the head noun of the noun phrase]

Edman_degradation of intact_protein
beta-oxidation of fatty acid
56_Aubrey_hole inside circle

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## Pattern matching

- Syntactic structures Subject-Verb-Direct Object
or "lexons"
amino_acid_sequence show Bacillus_subtilis nucleotide_sequencing reveal heterozygosity Aubrey_Holes are inside bank


## Combination

- We consider the N prepositional structures with the highest rate selected previously
- We elect the structures Sub-Vb-Obj where the Subject and the Object both appear among those N structures


## Wrong relations

Altar Stone is in front
Heel stone leans of vertical
Sarsen block are 1.4 metre
Stonehenge is of 35 foot
heel stone is from ring
120 foot from ring
Two of Station Stone
central part of monument
rectangle to midsummer sunrise line of monument

- Incomplete
- Uninformative
- Irrelevant



## Examples

- "part of" basic relations
bottom of stone
shape of stone
block of sandstone
- spatial relations
ring of bluestones
center of circle
sandstone on Marlborough Downs
Preseli Mountain in Pembrokeshire
- disposition of the stones

Bluestone circle outside Trilithon horseshoe
Bluestone circle inside Sarsen Circle
Bluestone circle is added outside Trilithon horseshoe
Slaughter Stone is made of sarsen
100 foot diameter circle of 30 sarsen stone

## Correct relations we didn't use

Aubrey Holes vary from 2 to 4 foot in depth
8 -ton Heel Stone is on main axis at focus
Sarsen stone are from Marlborough Down
Stonehenge stands on open downland of Salisbury Plain
bluestone came from Preselus Mountain in southwestern Wale
monument comprises of several concentric stone arrangement
Heel Stone is surrounded by circular ditch
third trilithon stone bears of distinguished human head
carving on twelve stone
trilithon linteled of large sarsen stone
Three Trilithon are now complete with lintel

- Provenance - locations
- Sizes - weight
- Details (carvings)

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## Results

- What we get: positions sizes weights composition (shape)
- Double checking of some information possible due to different descriptions and/or different patterns relevant on the same phrase
- World knowledge lacking
- Information uncomplete


## WebSites

- http://kaon.semanticweb.org/frontpage
- http://www.ontoknowledge.org
- http://www.ontolearn.de
- http://wise.vub.ac.be/ontobasis
- http://www.cnts.ua.ac.be/cgi-bin/ontobasis

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