Lecture 3.1: Machine Learning for Named Entity Recognition

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The who, where, when & how much in a sentence

- The task: identify lexical and phrasal information in text which express references to named entities NE, e.g.,
  - person names
  - company/organization names
  - locations
  - dates&times
  - percentages
  - monetary amounts
- Determination of an NE
  - Specific type according to some taxonomy
  - Canonical representation (template structure)

Example of NE-annotated text

Delimit the named entities in a text and tag them with NE types:

<ENAMEX TYPE=„LOCATION“>Italy</ENAMEX>‘s business world was rocked by the announcement <TIMEX TYPE=„DATE“>last Thursday</TIMEX> that Mr. <ENAMEX TYPE=„PERSON“>Verdi</ENAMEX> would leave his job as vice-president of <ENAMEX TYPE=„ORGANIZATION“>Music Masters of Milan, Inc</ENAMEX> to become operations director of <ENAMEX TYPE=„ORGANIZATION“>Arthur Andersen</ENAMEX>.

- „Milan“ is part of organization name
- „Arthur Andersen“ is a company
- „Italy“ is sentence-initial $\Rightarrow$ capitalization useless

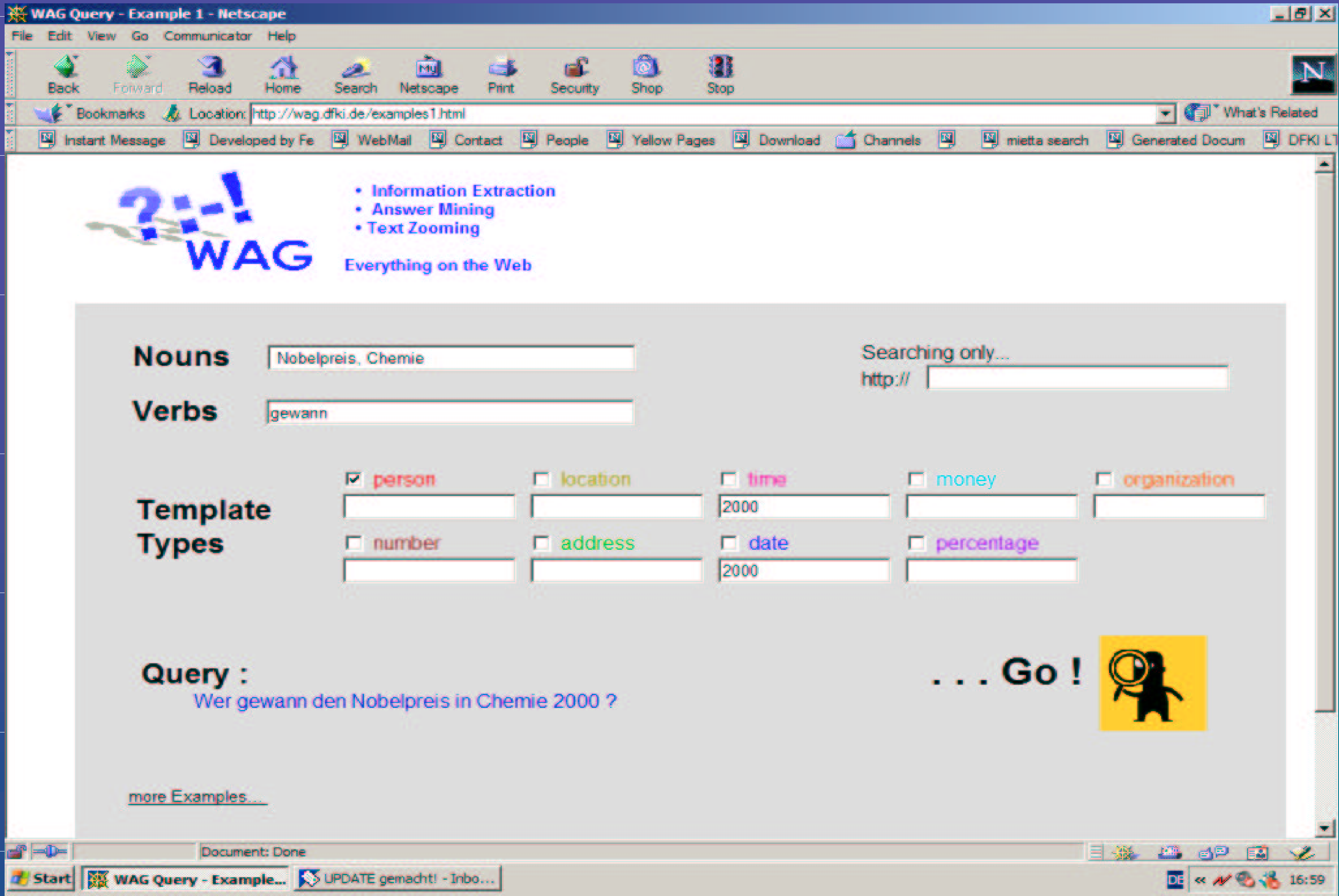
NE and Question-Answering

- Often, the expected answer type of a question is a NE
  - *What was the name of the first Russian astronaut to do a spacewalk?*
    - Expected answer type is PERSON
  - *Name the five most important software companies!*
    - Expected answer type is a list of COMPANY
  - *Where is does the ESSLLI 2004 take place?*
    - Expected answer type is LOCATION (subtype COUNTRY or TOWN)
  - *When will be the next talk?*
    - Expected answer type is DATE

German Named Entity

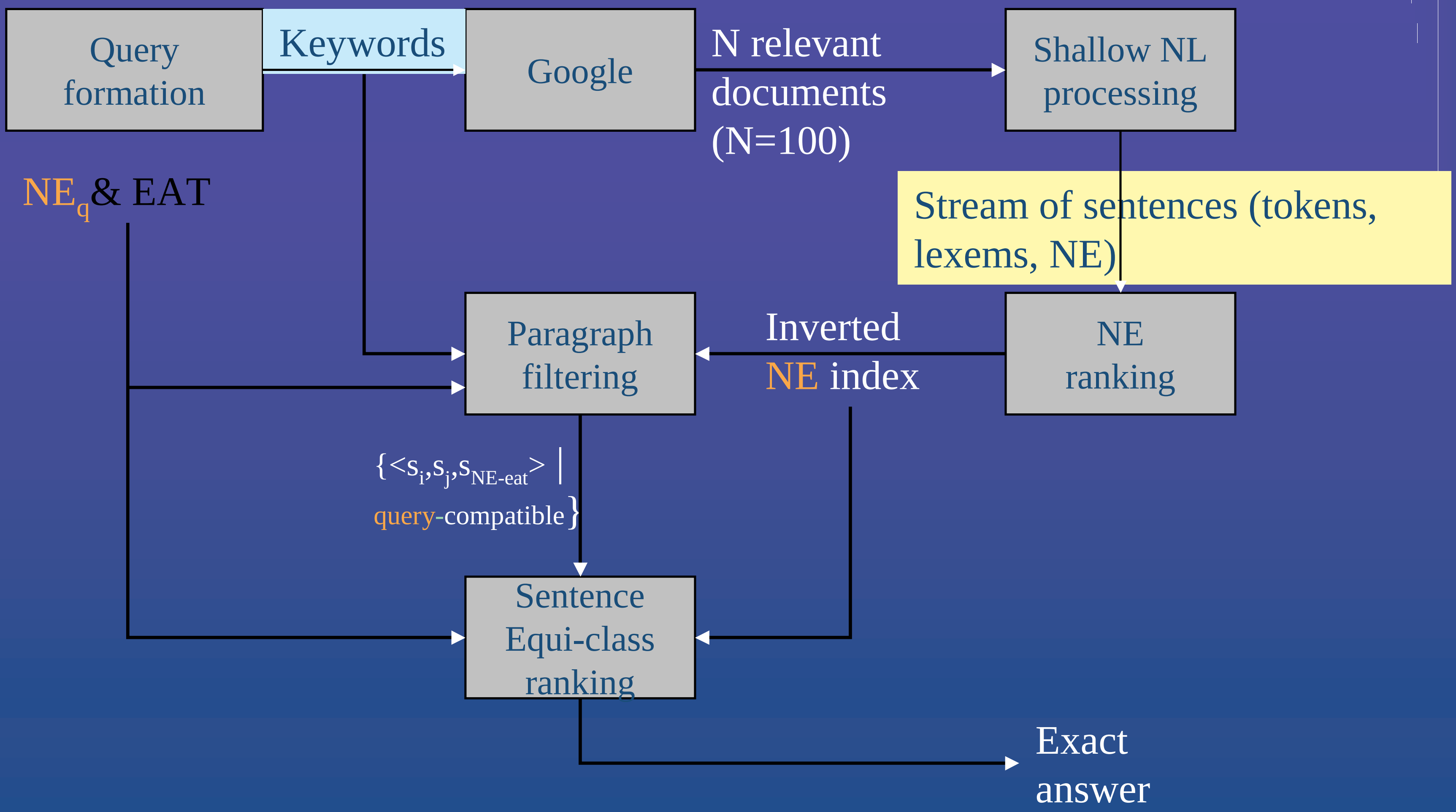
System Demo

NE and Web Mining: DFKI System WAG



The Result is an Indexed List of Named Entities

WAG's Control Flow



Average Results (40 Questions)

Metric	Exact Answer	Sentence Answer	Google Snippet
MRR (N=5)	**0.174**	**0.171**	**0.0975**
Recall (Top 1)	**0.38**	**0.38**	**0.255**
Recall (Top 3)	**0.48**	**0.46**	**0.435**

Difficulties of Automatic NER

- Potential set of NE is too numerous to include in dictionaries/Gazetteers
- Names changing constantly
- Names appear in many variant forms
- Subsequent occurrences of names might be abbreviated

⇒ list search/matching does not perform well
⇒ context based pattern matching needed

Difficulties for Pattern Matching Approach

Whether a phrase is a named entity, and what name class it has, depends on

- Internal structure:
  „Mr. Brandon“
- Context:
  „The new company, SafeTek, will make air bags.“
- Feiyu Xu, researcher at DFKI, Saarbrücken

NE and chunk parsing

- POS tagging plus generic chunk parsing alone does not solve the NE problem (ignoring type assignment for the moment)
  - Complex modification; target structure
    - [[1 Komma 2]   Mio Euro]
      CARD NN CARD NN NN
  - POS tagging and chunk parsing would construct following syntactical possible but wrong structure
    - [1 Komma] [2   Mio] [Euro]

NE and chunk parsing

- Postmodification
  - Date expression with target structure
    - Am [3. Januar 1967]
      CARD NN CARD
  - Wrong structure when generic chunk parsing
    - Am [3. Januar] [1967]
      CARD NN CARD

NE and chunk parsing

- Coordination of unit measures
  - target structure
    - [6 Euro und 50 Cents]
      CARD NN KON CARD NN
  - Generic chunk analysis
    - [6 Euro] und [50 Cents]
      CARD NN KON CARD NN

NE and chunk parsing

- Person names
  - Target structure
    - [John F. Kennedy]
      NE NE NE
  - Generic chunk parsing
    - [John F.] [Kennedy]
      NE NE NE

NE Co-reference

Norman Augustine ist im Grunde seines Herzens ein friedlicher Mensch."Ich könnte niemals auf irgend etwas schiessen", versichert der 57jährige Chef des US-Rüstungskonzerns Martin Marietta Corp. (MM). ... Die Idee zu diesem Milliardendeal stammt eigentlich von GE-Chef JohnF. Welch jr. Er schlug Augustine bei einem Treffen am 8. Oktober den Zusammenschluss beider Unternehmen vor. Aber Augustine zeigte wenig Interesse, Martin Marietta von einem zehnfach grösseren Partner schlucken zu lassen.

- Martin Marietta can be a person name or a reference to a company
- If MM is not part of an abbreviation lexicon, how do we recognize it?
  - Also by taking into account NE reference resolution.

NE is an interesting problem

- Productivity of name creation requires lexicon free pattern recognition
- NE ambiguity requires resolution methods
- Fine-grained NE classification needs fined-grained decision making methods
  - Taxonomy learning
- Multi-linguality
  - A text might contain NE expressions from different languages, e.g., output of IdentiFinder™

Why Machine Learning NE?

- System-based adaptation two new domains
  - Fast development cycle
  - Manual specification too expensive
  - Language-independence of learning algorithms
  - NL-tools for feature extraction available, often as open-source
- Current approaches already show near-human-like performance
  - Can easily be integrated with externally available Gazetteers
- High innovation potential
  - Core learning algorithms are language independent, which supports multi-linguality
  - Novel combinations with relational learning approaches
  - Close relationship to currently developed ML-approaches of reference resolution

Different approaches

- Different degree of NL-preprocessing
  - Character-level features (Whitelaw&Patrick, CoNLL, 2003)
  - Tokenization (Bikel et al., ANLP 1997)
  - POS + lemmatization (Yangarber et al. Coling 2002)
  - Morphology (Cucerzan&Yarowsky, EMNLP 1999)
  - Full parsing (Collins&Singer, EMNLP 1999)
- Supervised learning
  - Training is based on available very large annotated corpus
  - Mainly statistical-based methods used
    - HMM, MEM, connectionists models, SVM, hybrid ML-methods (cf. http://cnts.uia.ac.be/conll2003/ner/)
- Unsupervised learning
  - Training only needs very few seeds and very large un-annotated corpus: Topic of this lecture

Current performance of supervised methods (CoNLL, 2003)*

English	precision	recall	F
[FIJZ03]	88.99%	88.54%	88.76±0.7
[CN03]	88.12%	88.51%	88.31±0.7
[KSNM03]	85.93%	86.21%	86.07±0.8
[ZJ03]	86.13%	84.88%	85.50±0.9
[CMP03b]	84.05%	85.96%	85.00±0.8
[CC03]	84.29%	85.50%	84.89±0.9
[MMP03]	84.45%	84.90%	84.67±1.0
[CMP03a]	85.81%	82.84%	84.30±0.9
[ML03]	84.52%	83.55%	84.04±0.9
[BON03]	84.68%	83.18%	83.92±1.0
[MLP03]	80.87%	84.21%	82.50±1.0
[WNC03]*	82.02%	81.39%	81.70±0.9
[WP03]	81.60%	78.05%	79.78±1.0
[HV03]	76.33%	80.17%	78.20±1.0
[DD03]	75.84%	78.13%	76.97±1.2
[Ham03]	69.09%	53.26%	60.15±1.3
baseline	71.91%	50.90%	59.61±1.2

German	precision	recall	F
[FIJZ03]	83.87%	63.71%	72.41±1.3
[KSNM03]	80.38%	65.04%	71.90±1.2
[ZJ03]	82.00%	63.03%	71.27±1.5
[MMP03]	75.97%	64.82%	69.96±1.4
[CMP03b]	75.47%	63.82%	69.15±1.3
[BON03]	74.82%	63.82%	68.88±1.3
[CC03]	75.61%	62.46%	68.41±1.4
[ML03]	75.97%	61.72%	68.11±1.4
[MLP03]	69.37%	66.21%	67.75±1.4
[CMP03a]	77.83%	58.02%	66.48±1.5
[WNC03]	75.20%	59.35%	66.34±1.3
[CN03]	76.83%	57.34%	65.67±1.4
[HV03]	71.15%	56.55%	63.02±1.4
[DD03]	63.93%	51.86%	57.27±1.6
[WP03]	71.05%	44.11%	54.43±1.4
[Ham03]	63.49%	38.25%	47.74±1.5
baseline	31.86%	28.89%	30.30±1.3

*http://cnts.uia.ac.be/conll2003/ner/

Main features used by CoNLL 2003 systems

	lex	pos	aff	pre	ort	gaz	chu	pat	cas	tri	bag	quo	doc
Florian	+	+	+	+	+	+	+	-	+	-	-	-	-
Chieu	+	+	+	+	+	+	-	-	-	+	-	+	+
Klein	+	+	+	+	-	-	-	-	-	-	-	-	-
Zhang	+	+	+	+	+	+	+	-	-	+	-	-	-
Carreras (a)	+	+	+	+	+	+	+	+	-	+	+	-	-
Curran	+	+	+	+	+	+	-	+	+	-	-	-	-
Mayfield	+	+	+	+	+	-	+	+	-	-	-	+	-
Carreras (b)	+	+	+	+	+	-	-	+	-	-	-	-	-
McCallum	+	-	-	-	+	+	-	+	-	-	-	-	-
Bender	+	+	-	+	+	+	+	-	-	-	-	-	-
Munro	+	+	+	-	-	-	+	-	+	+	+	-	-
Wu	+	+	+	+	+	+	-	-	-	-	-	-	-
Whitelaw	-	-	+	+	-	-	-	-	+	-	-	-	-
Hendrickx	+	+	+	+	+	+	+	-	-	-	-	-	-
De Meulder	+	+	+	-	+	+	+	-	+	-	-	-	-
Hammerton	+	+	-	-	-	+	+	-	-	-	-	-	-

Table 3: Main features used by the the sixteen systems that participated in the CoNLL-2003 shared task sorted by performance on the English test data. Aff: affix information (n-grams); bag: bag of words; cas: global case information; chu: chunk tags; doc: global document information; gaz: gazetteers; lex: lexical features; ort: orthographic information; pat: orthographic patterns (like Aa0); pos: part-of-speech tags; pre: previously predicted NE tags; quo: flag signing that the word is between quotes; tri: trigger words.

Learning Approaches in CoNLL

- Most systems used
  - Maximum entropy modeling (5)
  - Hidden-Markov models (4)
  - Connectionists methods (4)
- Near all systems used external resources, e.g., gazetteers
- Best systems performed hybrid learning approach

Details of Two Unsupervised NE Learning Methods

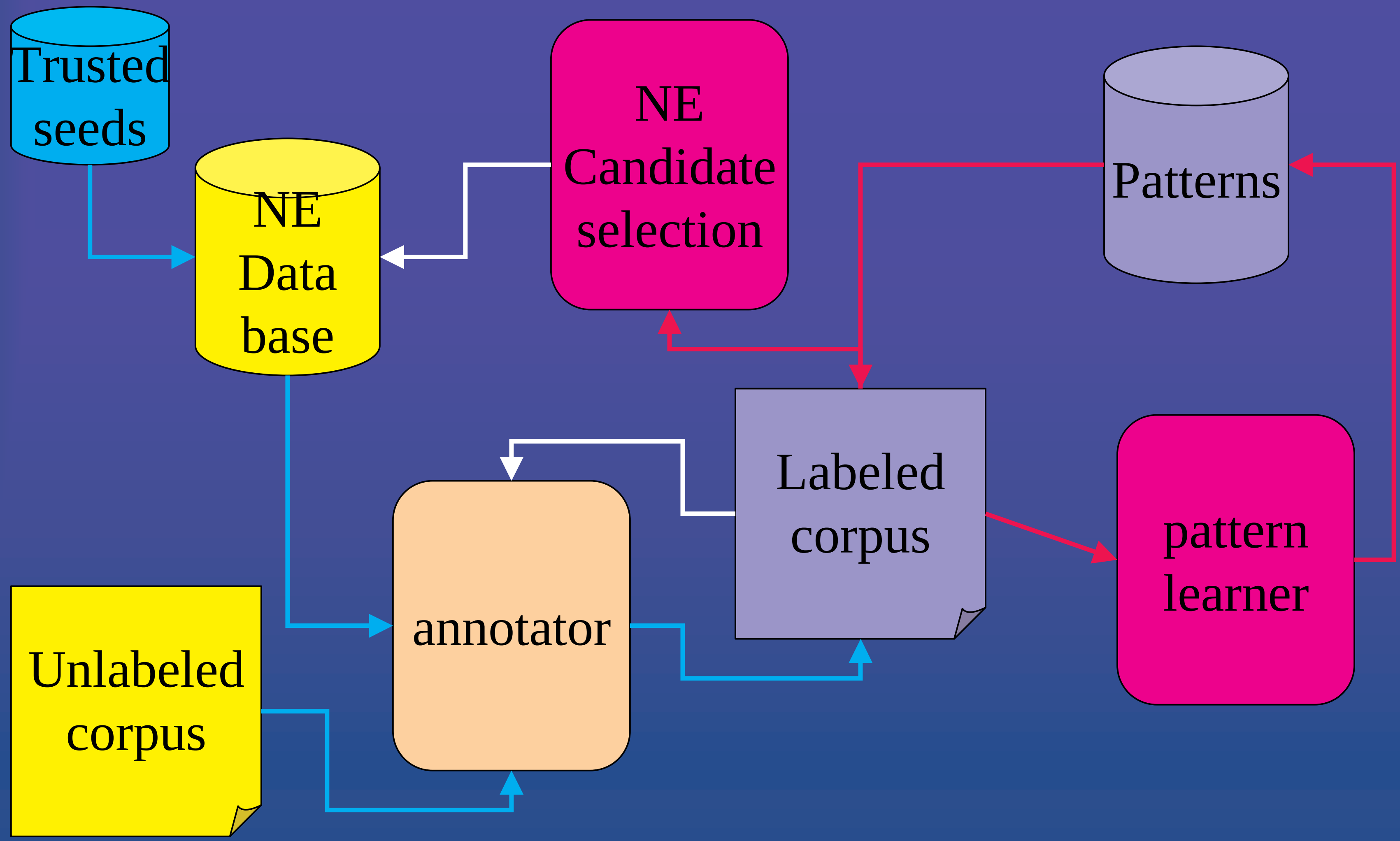
- Unsupervised NE Classification
  - Michael Collins and Yoran Singer, 1999

- Unsupervised Learning of Generalized Names
  - Yangarber, Lin, Grishman, 2002
  - Lin, Yangarber, Grishman, 2003

Unsupervised NE: idea

- Define manually only a small set of trusted seeds
- Training then only uses un-labeled data
- Initialize system by labeling the corpus with the seeds
- Extract and generalize patterns from the context of the seeds
- Use the patterns to further label the corpus and to extend the seed set (bootstrapping)
- Repeat the process unless no new terms can be identified

Unsupervised NE-learning: idea



Unsupervised NE classification

based on Michael Collins and Yoran Singer, EMNLP 1999

- The task: to learn a decision list to classify strings as person, location or organization

The learned decision list is an ***ordered*** sequence of if-then rules

… says Mr. Gates, founder of Microsoft …

R_1 : if features then person
R_2 : if features then location
R_3 : if features then organization
…
R_n : if features then person

… says Mr. Gates, founder of Microsoft …

Outline of Unsupervised Co-Training

- Parse an unlabeled document set
- Extract each NP, whose head is tagged as proper noun
- Define a set of relevant features, which can be applied on extracted NPs
- Define two separate types of rules on basis of feature space
- Determine small initial set of seed rules
- Iteratively extend the rules through co-training

Two Categories of Rules

- The key to the method is redundancy in the two kind of rules.

…says Mr. Cooper, a vice president of…

Paradigmatic or spelling

Syntagmatic or contextual

Huge amount of unlabeled data gives us these hints!

The Data

- 971,746 New York Times sentences were parsed using full sentence parser.
- Extract consecutive sequences of proper nouns (tagged as NNP and NNPS) as named entity examples if they met one of following two criterion.
- Note: thus seen, NNP(S) functions as a generic NE-type, and the main task is now to sub-type it.

Kinds of Noun Phrases

1. There was an appositive modifier to the NP, whose head is a singular noun (tagged NN).
   - *…says [Maury Cooper], [a vice president]…*

2. The NP is a complement to a preposition which is the head of a PP. This PP modifies another NP whose head is a singular noun.
   - *… fraud related to work on [a federally funded sewage plant] [in [Georgia]].*

(spelling, context) pairs created

- *…says Maury Cooper, a vice president…*
  - (Maury Cooper, president)
- *… fraud related to work on a federally funded sewage plant in Georgia.*
  - *(Georgia, plant_in)*

Features

for representing examples for the learning algorithm

- Set of spelling features
  - Full-string=x (full-string=Maury Cooper)
  - Contains(x) (contains(Maury))
  - Allcap1 IBM
  - Allcap2 N.Y.
  - Nonalpha=x A.T.&T. (nonalpha=..&.)

- Set of context features
  - Context = x (context = president)
  - Context-type = x appos or prep

It is strongly assumed that the features can be partitioned into two types such that each type alone is sufficient for classification

Examples of named entities and their features

Sentence	Entities(Spelling/Context)	(Active) Features
But Robert Jordan, a partner at Steptoe & Johnson who took …	Robert Jordon/partner	Full-string=Robert_Jordan, contains(Robert), contains(Jordan), context=partner, context-type=appos
	Steptoe & Johnson/partner_at	Full-string=Steptoe_&_Johnson, contains(Steptoe), contains(&), contains(Johnson), nonalpha=& , context=partner_at, context-type=prep
By hiring a company like A.T.&T. …	A.T.&T./company_like	Full-string= A.T.&T., allcap2, nonalpha=..&. , context=company_like, context-type=prep
Hanson acquired Kidde Incorporated, parent of Kidde Credit, for …	Kidde Incorporated/parent	Full-string=Kidde_Incorporated, contains(Kidde), contains(Incorporated), context=parent, context-type=appos
	Kidde Credit/parent_of	Full-string=Kidde_Credit, contains(Kidde), contains(Credit), context=parent_of, context-type=prep

Rules

Two separate types of rules:
Spelling rules
Context rules

Feature → NE-type, h(Feature,NE-type)

h(x,y): the strength of a rule, defined as

$$\arg\max_{x,y} \frac{Count(x,y)+\alpha}{Count(x)+k\alpha}$$

where

$$Count(x) = \sum_{y \in Y} Count(x,y)$$

α is a smoothing parameter

k = #NE-types

Is an estimate of the conditional probability of the NE-type given the feature, P(y|x)

The rules ordered according to their strengths h form a decision list: the sequence of rules are tested in order, and the answer to the ***first*** satisfied rule is output.

7 SEED RULES

- Full-string = New York → Location
- Full-string = California → Location
- Full-string = U.S. → Location
- Contains(Mr.) → Person
- Contains(Incorporated) → Organization
- Full-string=Microsoft → Organization
- Full-string=I.B.M. → Organization

> Note: only one type of rules used as seed rules, and all NE-types should be covered

The Co-training algorithm

1. Set N=5 (max. # of rules of each type induced in each iteration)
2. **Initialize**: Set the spelling decision list equal to the set of seed rules. Label the training set using these rules.
3. Use these to get contextual rules. (x = feature, y = label)
   1. Compute h(x,y), and induce at most N * K rules
   2. all must be above some threshold p_{min}=0.95
4. Label the training set using the contextual rules.
5. Use these to get N*K spelling rules (same as step 3.)
6. Set spelling rules to seed plus the new rules.
7. If N < 2500, set N=N+5, and goto step 3.

8. Label the training data with the combined spelling/contextual decision list, then induce a final decision list from the labeled examples where all rules (regardless of strength) are added to the decision list.

Example

- (IBM, company)
  - …IBM, the company that makes…
- (General Electric, company)
  - ..General Electric, a leading company in the area,…
- (General Electric, employer)
  - … joined General Electric, the biggest employer…
- (NYU, employer)
  - NYU, the employer of the famous Ralph Grishman,…

Why Separate Spelling, Context Features?

Can use theory behind co-training to explain how algorithm works

Requirements:

1. Classification problem $f: X \rightarrow Y$
   1. $f_1(x_{1,i}) = f_2(x_{2,i}) = y_i$ for $i = 1 \ldots m$
   2. $f_1(x_{1,i}) = f_2(x_{2,i})$ for $i = m+1 \ldots n$

   (softer criteria requires f_1 and f_2 to minimize the disagreements → similarity)
2. Can partition features X into 2 types of features $x = (x_1,x_2)$
3. Each type is sufficient for classification
4. x_1,x_2 not correlated to tightly (e.g., no deterministic function from x_1 to x_2)

f_i must correctly classify labeled examples, and

must agree with each other on unlabeled ex.

Open question: best similarity function?

3. & 4. Say that features can be partitioned.

The Power of the Algorithm

- Greedy method
  - At each iteration method increases number of rules
  - While maintaining a high level of agreement between spelling & context rules

For n= 2500:

1. The two classifiers give both labels on 49.2% of the unlabeled data
2. And give the *same* label on 99.25% of these cases

➢ The algorithm maximizes the number of unlabeled examples on which the two decision list agree.

Evaluation

- 88,962 (spelling, context) pairs.
  - 971,746 sentences
- 1,000 randomly extracted to be test set.
- Location, person, organization, noise (items outside the other three)
- 186, 289, 402, 123 (- 38 temporal noise).
- Let N_c be the number of correctly classified examples
  - Noise Accuracy: N_c / 962
  - Clean Accuracy: N_c /(962-85)

Results

Algorithm	Clean Accuracy	Noise Accuracy
Baseline	45.8%	41.8%
EM	83.1%	75.8%
Yarowsky 95	81.3%	74.1%
Yarowsky Cautious	91.2%	83.2%
DL-CoTrain	91.3%	83.3%
CoBoost	91.1%	83.1%

Remarks

- Needs full parsing of unlabeled documents
  - Restricted language independency
  - Need linguistic sophistication for new types of NE
- Slow training
  - In each iteration, full size of training corpus has to be re-labeled
- DFKI extensions
  - Typed Gazetteers
  - Chunk parsing only
  - Integrated into a cross-language QA system

Unsupervised Learning of Generalized Names

Yangarber, Lin, Grishman, Coling 2002 & Lin, Yangarber, Grishman, ICML 2003

- Much work on ML-NE focuses on classifying *proper names (PNs)*
  - Person/Location/Organization
- IE generally relies on domain-specific lexicon or *Generalized Names (GNs)*
  - Closer to terminology:
    single- or multi-word domain-specific expressions
- Automatic learning of GNs is an important first step towards truly adaptive IE
  - IE system that can automatically adapt itself to new domains

How GNs differ from PNs

- Not necessary capitalized
  - tuberculosis
  - E. coli
  - Ebola haemorrhagic fever
  - Variant Creutzfeldt-Jacob disease
- Name boundaries are non-trivial to identify
  - "the four latest typhoid fever cases"
- Set of possible candidate names is broader and more difficult to determine
  - "<u>National Veterinary Services</u> Director <u>Dr. Gideon Bruckner</u> said no cases of <u>mad cow disease</u> have been in <u>South Africa</u>."
- Ambiguity
  - E. coli : organism or disease
  - Encephalitis : disease or symptom

NOMEN: the Learning Algorithm

1. <u>Input</u>: Seed names in several chosen categories
2. Tag occurrences of names
3. Generate local patterns around tags
4. Match patterns elsewhere in corpus
    1. Acquire top-scoring pattern(s)
5. Acquired patterns tags new names
    1. Acquire top-scoring name(s)
6. Repeat

Pre-processing

- Text-Zoner
  - Extract textual content
  - Strips of headers, footers etc.
- Tokenizer
  - Produces lemmas
- POS tagger
  - Statistically trained on WSJ
  - Unknown or foreign words are not lemmatized and tagged as noun

Seeds

- For each *target* category select N initial *trusted* seeds
  - Diseases:
    - Cholera, dengue, anthrax, BSE, rabies, JE, Japanese encephalitis, influenza, Nipah virus, FMD
  - Locations:
    - United States, Malaysia, Australia, Belgium, China, Europe, Taiwan, Hong Kong, Singapore, France
  - Others
    - Case, health, day, people, year, patient, death, number, report, farm
- Use frequency counts computed form corpus or some external data-base
- Many more additonal categories can be defined

Positive vs. Negative Seeds

- A seed name serves as
  - a positive example for its own class, and
  - a negative example for all other classes.

- Negative examples help steer the learner away from unreliable patterns
  - Competing classes
  - Termination of unsupervised learning

Pattern generation

- Tag every occurrence of each seed in corpus
  - "…new cases of <dis> cholera </dis> this year in …"
- For each tag, generate context rule: start/left-tag
  - [new case of <dis> cholera this year]
- Generalized left-side candidate patterns:
  - [new case of <dis> * * *]
  - [* case of <dis> * * *]
  - [* * of <dis> * * *]
  - [* * * <dis> cholera this year]
  - [* * * <dis> cholera this *]
  - [* * * <dis> cholera * *]

Pattern generation

- For each tag, generate context rule: end/right-tag
  - [case of cholera </dis> this year in]
- Generalized right-side candidate patterns:
  - [case of cholera </dis> * * *]
  - [* of cholera </dis> * * *]
  - [* * cholera </dis> * * *]
  - [* * * </dis> this year in]
  - [* * * </dis> this year *]
  - [* * * </dis> this * *]
- Note: all are potential patterns

Pattern application

- Apply each candidate pattern to corpus, observe where the pattern matches
  - E.g., the pattern [* * of <dis> * * *]
- Each pattern predicts one boundary: search for the partner boundary using a noun group NG regex:
  - [Adj* Noun+]
  - *"…distributed the yellow fever vaccine to the people"*
- The resulting NG can be (wrt. currently tagged corpus)
  - Positive: "…case <u>of</u> <dis> dengue </dis> …"
  - Negative: "…North <u>of</u> <loc> Malaysia </loc> …"
  - Unknown: "…symptoms <u>of</u> <?> swine fever </?> in …"

Identify candidate NGs

- Sets of NG that the pattern p matched
  - Pos = distinct matched NG types of correct category
  - Neg = distinct matched NG types of wrong category
  - Unk = distinct matched NGs of unknown category

Collect statistics for each pattern

$$acc(p) = \frac{|Pos|}{(|Pos| + |Neg|)}$$

$$conf(p) = \frac{|Pos| - |Neg|}{(|Pos| + |Neg| + |Unk|)}$$

Pattern selection

- Discard pattern p if acc(p) < θ
- The remaining patterns are ranked by
  - Score(p) = conf(p)*log|Pos(p)|
- Prefer patterns that:
  - Predict the correct category with less risk
  - Stronger support: match more distinct known names
- Choose top n patterns for each category
  - [* die of <dis> * * *]
  - [* vaccinate against <dis> * * *]
  - [* * * </dis> outbreak that have]
  - [* * * </dis> * * *]
  - [* case of <dis> * * *]

To get positive score, a pattern must have at least two distinct NGs as positive example, and more positive than negative exam.

Name selection

- Apply each accepted pattern to corpus, to find candidate names (using the NG)
  - “More people die of <dis> profound heartbreak than grief.”
- Rank each name type t based on quality of patterns that match it:

$$Rank(t) = 1 - \prod_{p \in M_t} (1 - conf(p))$$

M_t is the set of accepted patterns which match any of the instances of t

  - Require $|M_t| \geq 2 \Rightarrow$ t should appear ≥ 2 times
  - M_t contains at least on pattern predicting the left boundary of t and one pattern predicting the right boundary
  - Conf(p) assigns more credit to reliable patterns

Name selection

- Accept up to 5 top-ranked candidate names for each category
- Iterate learning algorithm until no more names can be learned
  - Bootstrap by using in each new iteration the extended set of new names to re-annotate the corpus

Salient Features of Nomen

- Generalized names
- A few manually-selected seeds
- Un-annotated corpus
- Un-restricted context (no syntactic restrictions)
- Patterns for left and right contexts independently
- Multiple categories simultaneously

Experiments

- Construction of reference lists for judging recall & precision of NOMEN

Compiled from multiple sources (medical DB, Web, manual review)

Appearing two or more time in development corpus

Manual list + acronyms + strip generic heads

Reference List	Disease	Location
Manual	2492	1785
Recall (26K)	322	641
Recall (100K)	616	1134
Precision	3588	2404

Score recal against recall list and precision against precision list; Distinguish type and token tests

Results

- Final recall & precision for 8 categories
  - Around 70% (in case of type-based evaluation)
  - Classical PN: Recall: 86-92%, Precision: above 70%
- Multi-class learning has positive effects
  - A category is less likely to expand beyond its true territory
  - The accepted names in each category serve as negative example for all categories
  - The learners avoid acquiring patterns with too many negatives
  - In some sense, the categories *self-tune* each other
- Comparison with human-in-the-loop
  - "More groups" can be as good as "few groups + human reviewer"
- Using a negative category (noun groups that belong to neither category, but generic terms), then also substantial increase in performance

Research Issues

- Can a richer linguistic model improve pattern generalization?
  - More elaborate NG-grammar
  - POS/SEM instead of wildcard
  - Note: one benefit of the approach is, that it does not need sophisticated linguistics, and hence is more adaptable
- How many different classes can effectively be learned simultaneously?
  - More complex seed-determination
  - When do the different classes enter into a dead-lock situation?
  - Group learning?
- At DKFI we have already started some of these inquiries

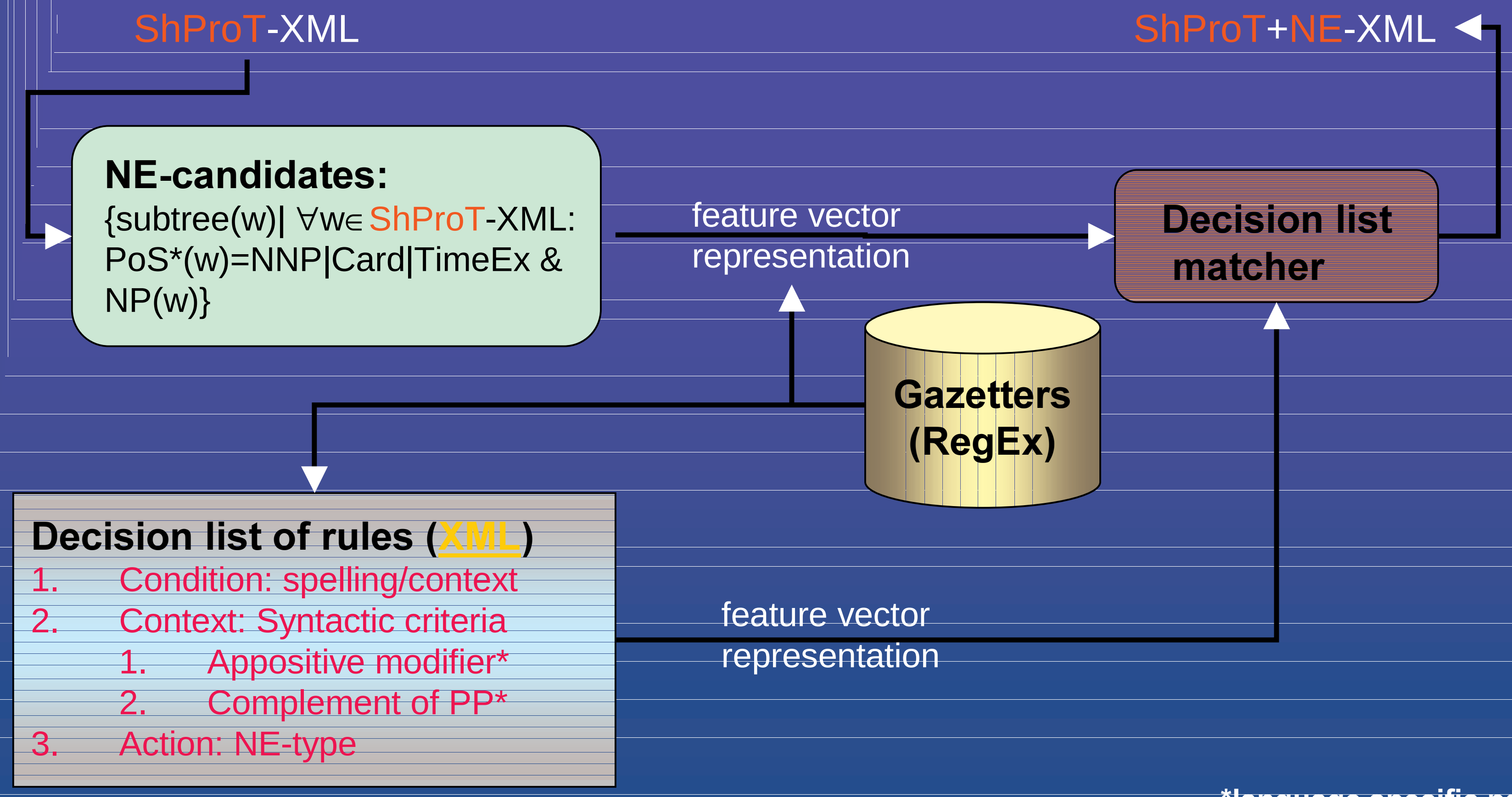
Final Remarks

- State-of-art in NE recognition
  - Machine learning works
  - Core learning engines are language independent
  - Feature extraction relies on language specific properties
  - Unsupervised learning promising direction

Challenging Problems

- What level of linguistic representation works best?
  - POS-tagging or deep parsing?
  - Employ linguistic principles (e.g., X-bar, head-principle, …)
- "language alignment"
  - Is it possible to re-use a model of language X, also for processing in language Y?
- Incremental learning algorithms
  - How to perform revision of learned patterns?
- Learning of fine-grained classes
  - Ako taxonomy learning, cf. Fleischman&Hovy, Coling2002
  - NE as Word Sense Disambiguation?
- Recognition of NE-paraphrases
  - NE-centered reference resolution
  - Combination of NE from un-structured and structured sources, cf. Cohen&Sarawagi, KDD'04, Seattle

Named Entity Recognition: DFKI-Version



*language specific part