Hybrid Information Extraction

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DFKI GmbH

Hybrid

- Is a system, if consists of different technologies
  - can be combined
  - each one depicts a solution by its own
  - the integration constitute an innovative plus for the whole system

Examples

Examples

hybrid engine

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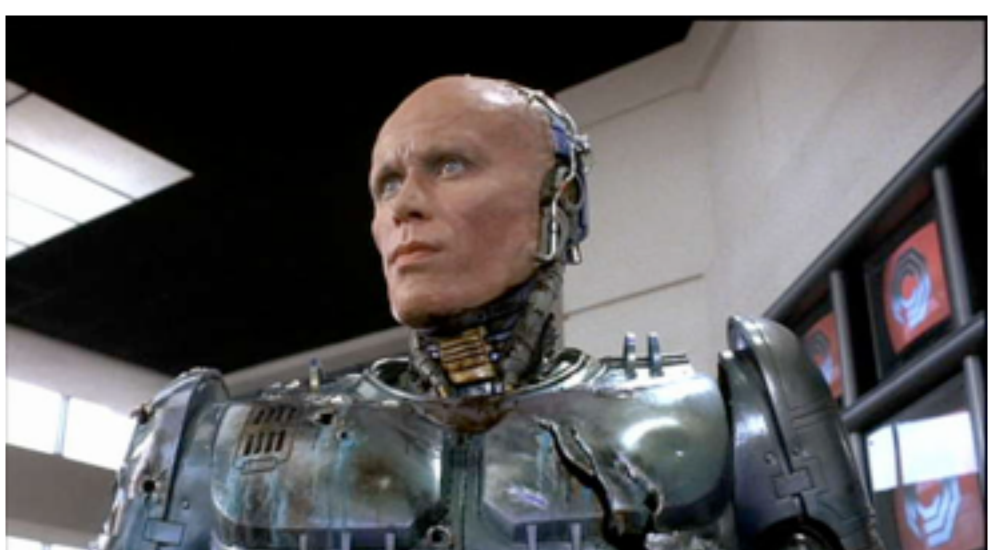
hybrid engine

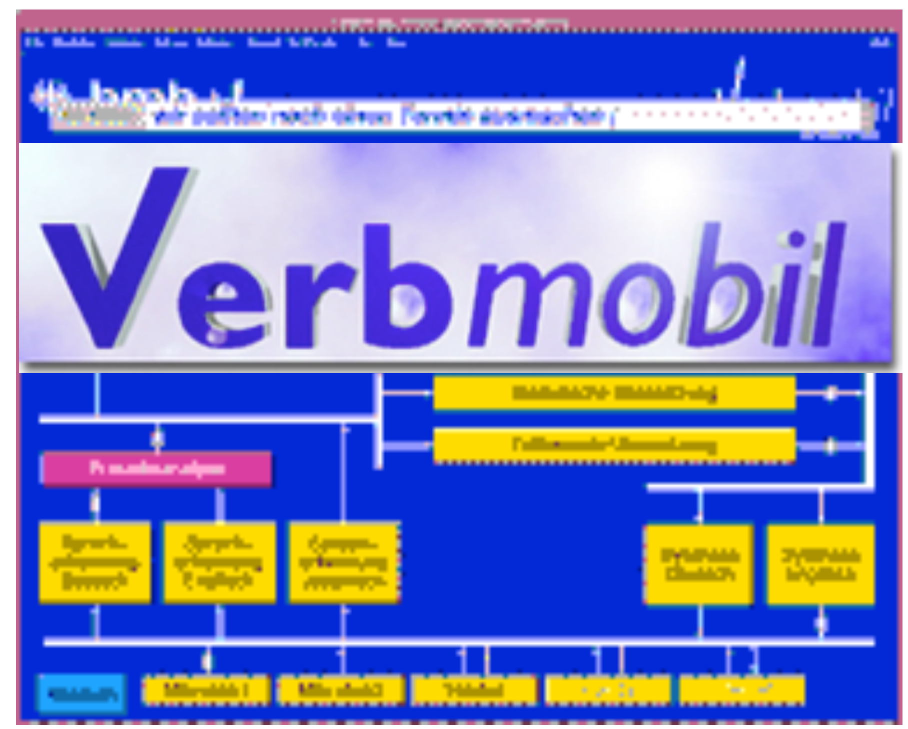
HumanMachine



Examples

hybrid engine

Hybrid Language Processing



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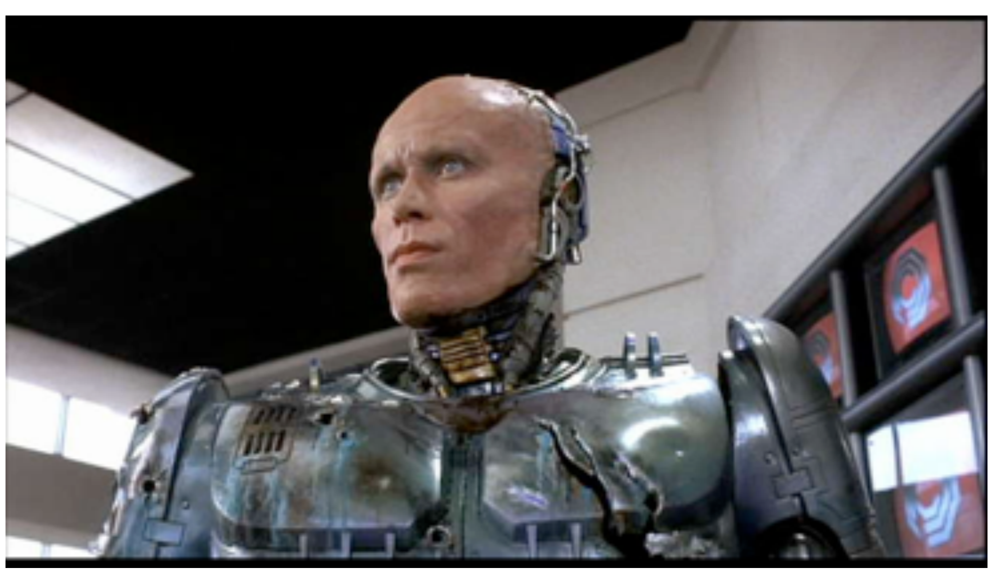

Information Extraction

- The aim of information extraction (IE) is the identification and structuring of domain specific information from free text by skipping irrelevant information at the same time.
- What counts as relevant is given to the system in form of pre-defined domain specific annotations, lexicon entries or rules.

Example: news about turnover

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turnover(Company, Year, Manner, Amount, Tendendcy, Differnce)

Unternehmen	Jahr	Größe	Betrag	Tendenz	Differenz
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- Early IE-systems were mainly rule-based (manual or learned) and the underlying methodology was specialized for specific applications, cf. MUC systems of the 90th.
- One result of the MUC challenges was a systematic division of labor into IE subtasks
  - Named-Entity Extraction (NER)
  - Relation Entity Extraction (REE)
  - Event Entity Extraction (EEE)
  - Coreferential analysis

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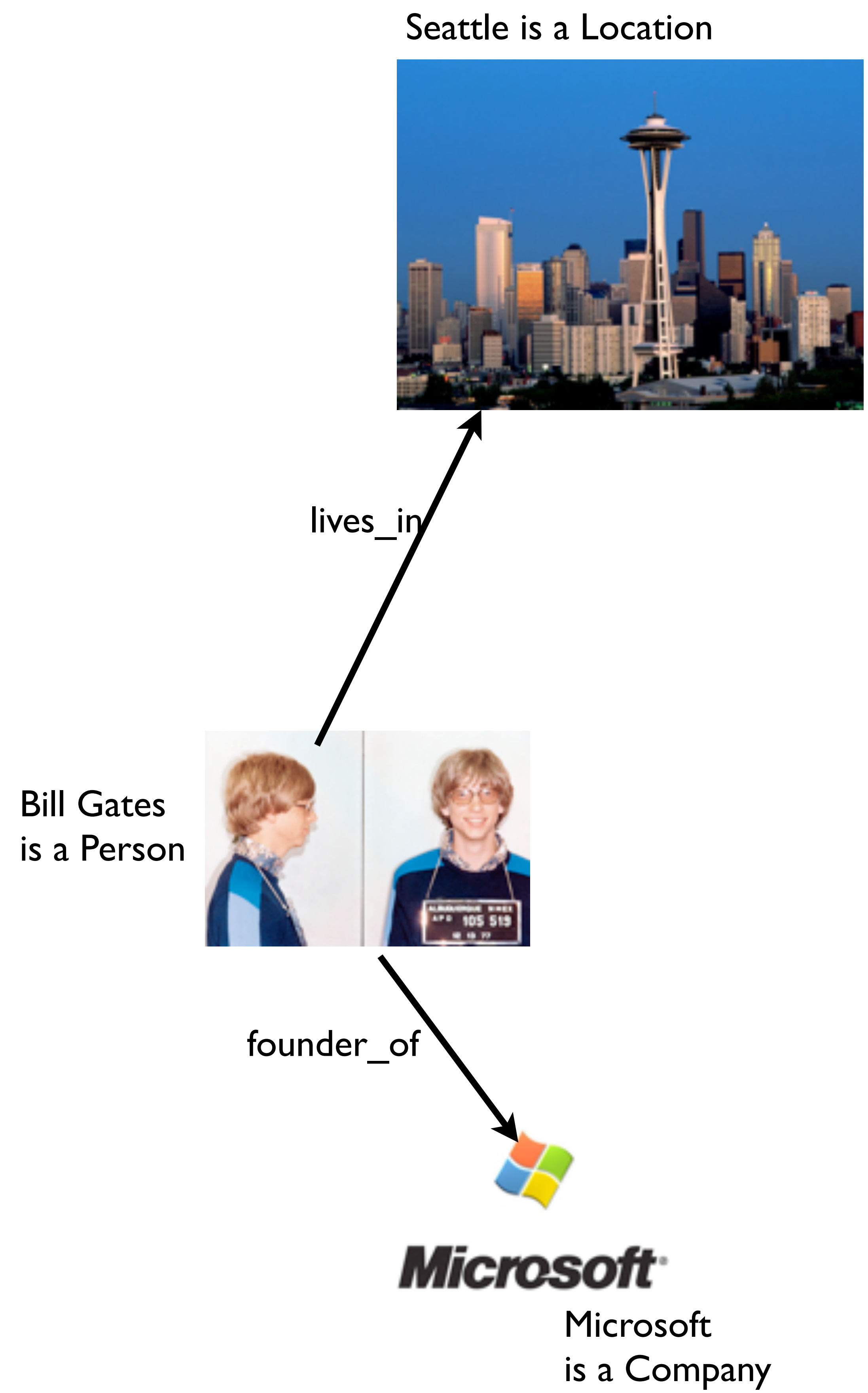

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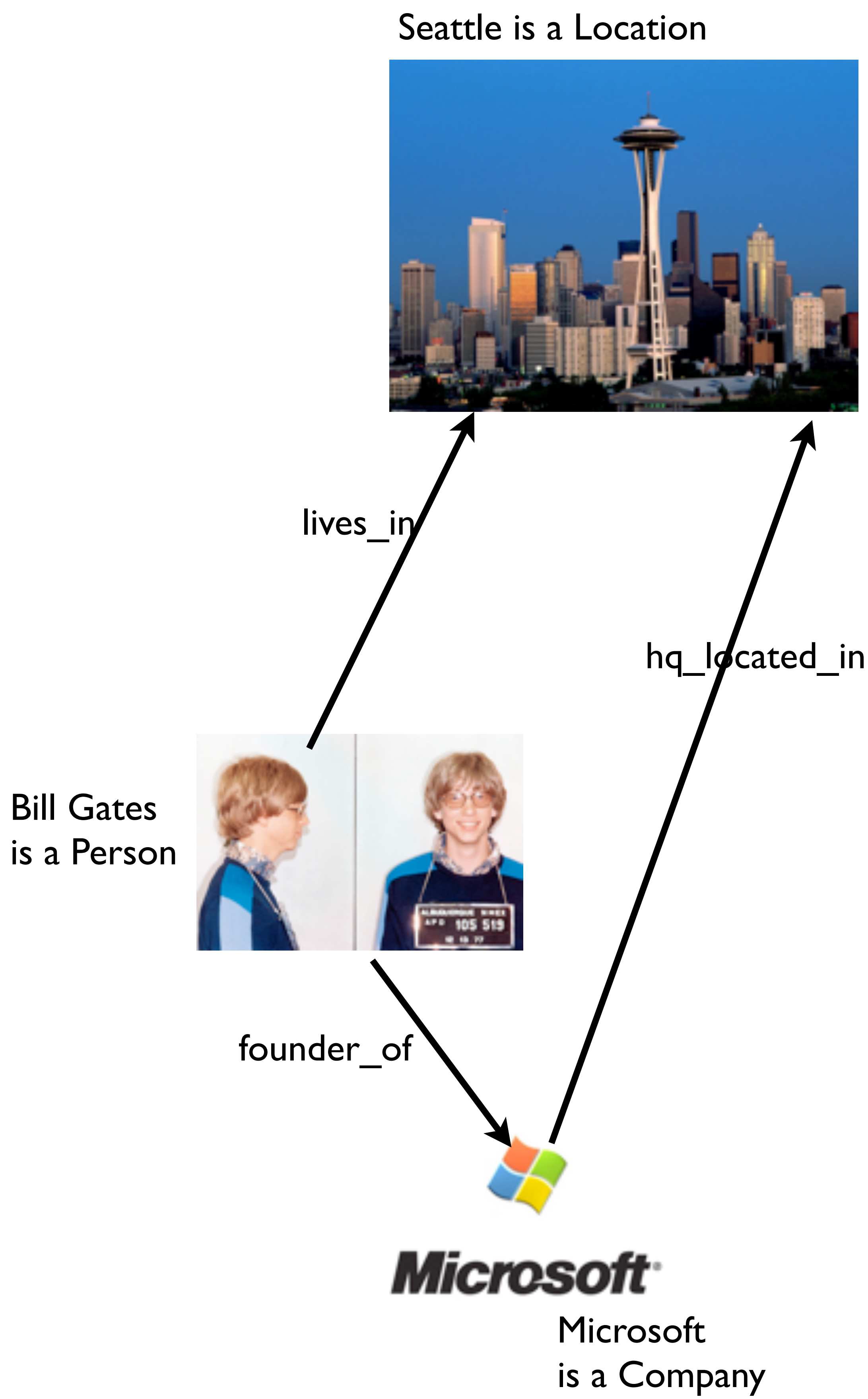

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IE - the Present

- There exists knowledge-based IE (KIE) and statistical IE (SIE)
- SIE is the State-of-the-Art in research, WIE in industry
- There exists a number of different strategies for the various IE-subtasks
  - from simple gazetteers to complex ontologies
  - from supervised, to minimal supervised to unsupervised Machine Learning algorithms
- Recently, the research focus is on NER, REE, Web-based IE, scalability, domain adaptivity, ...
- Open question: Which method is actually better suited for which text source, domain and application?

Hybrid IE

- Methods and strategies for the combination of different IE-components and the analysis of their plausibility.
- What are possible combinations ?

Multi-Strategy

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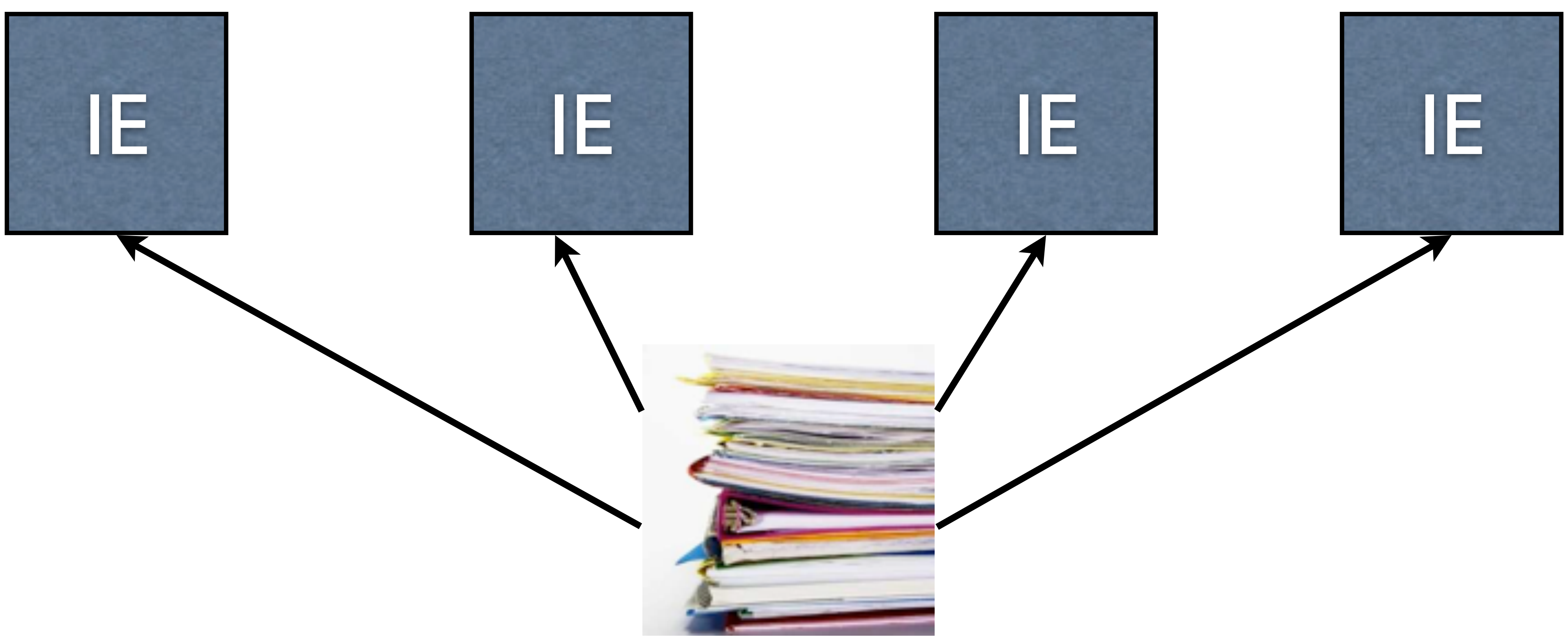

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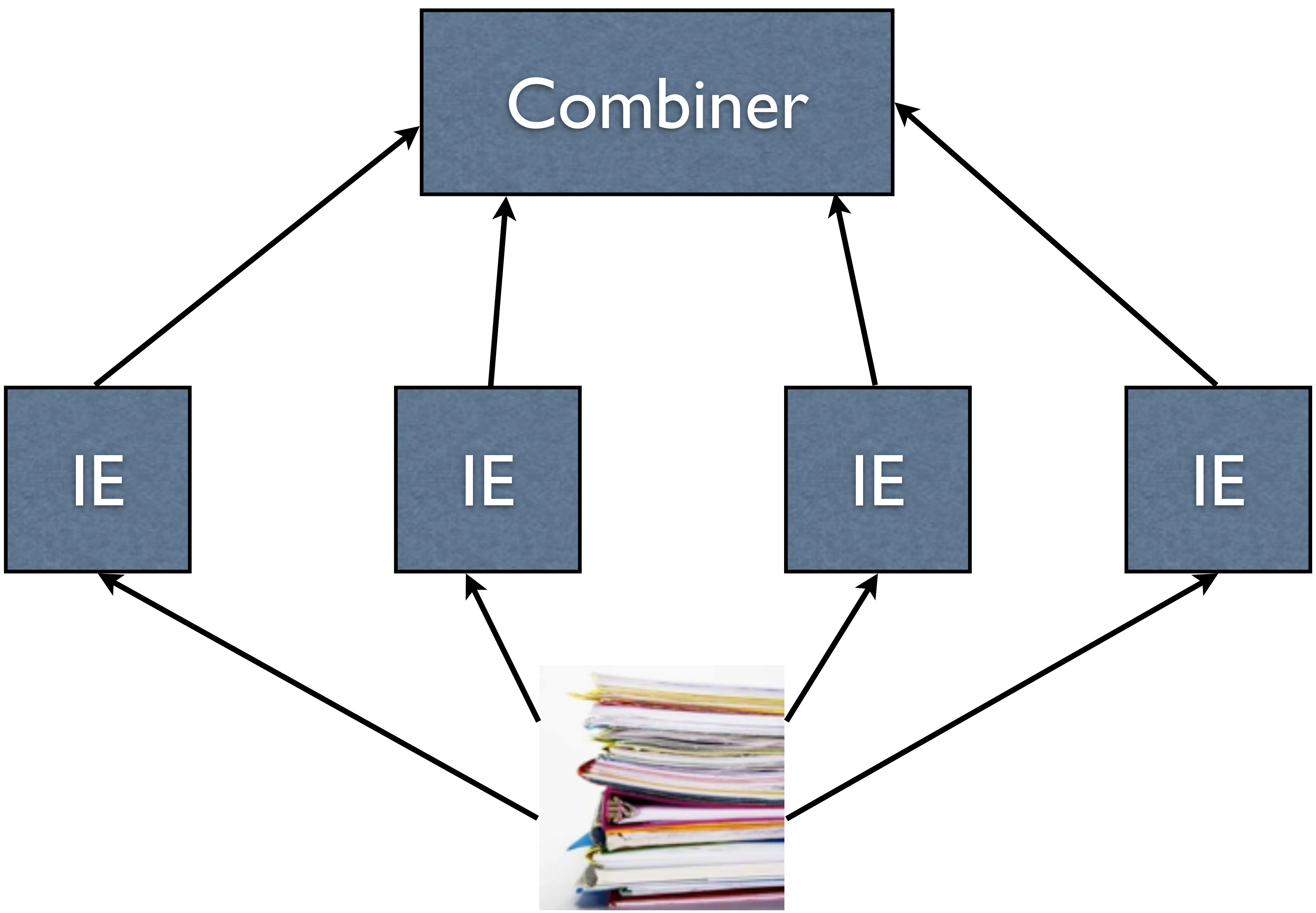

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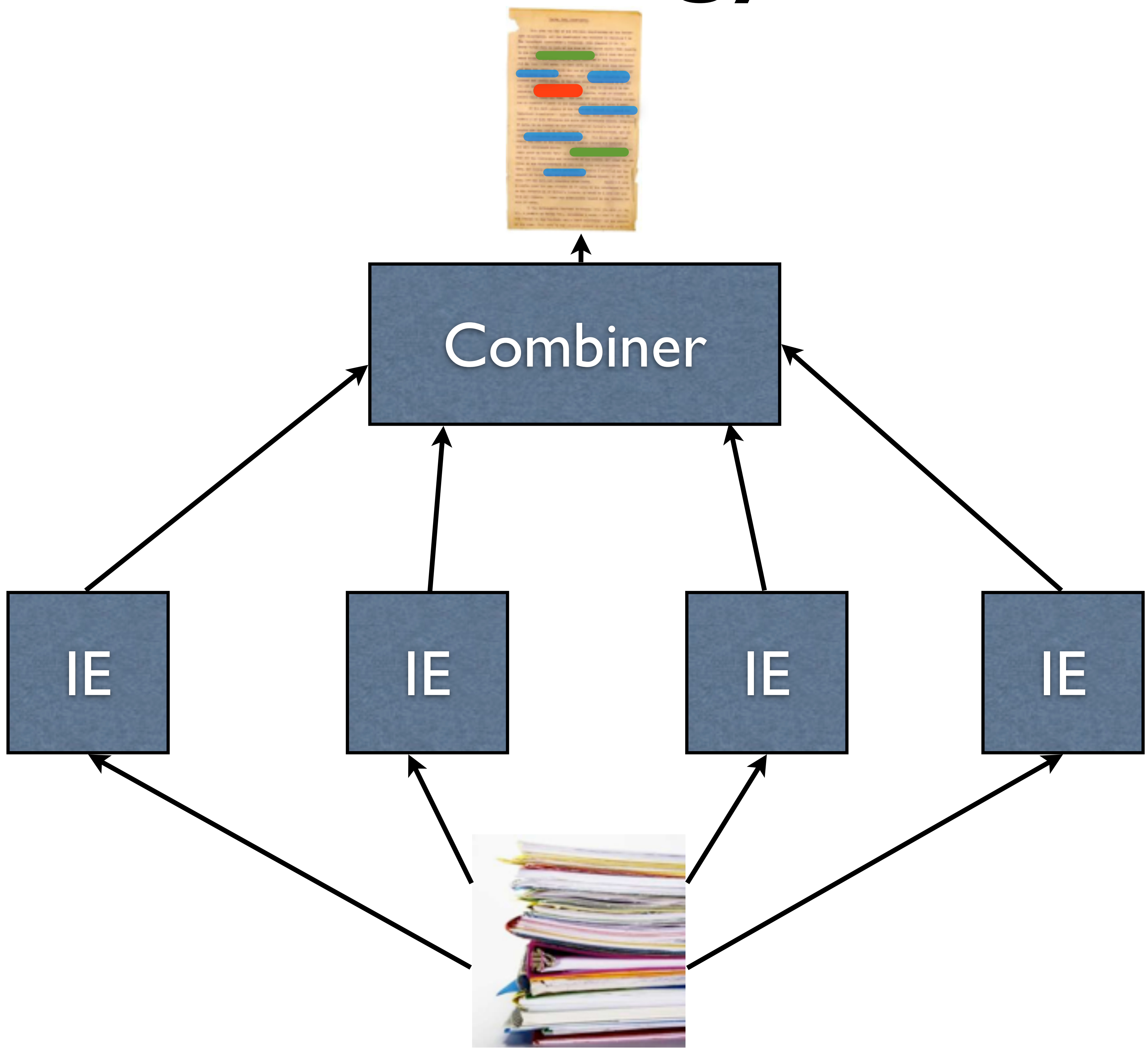
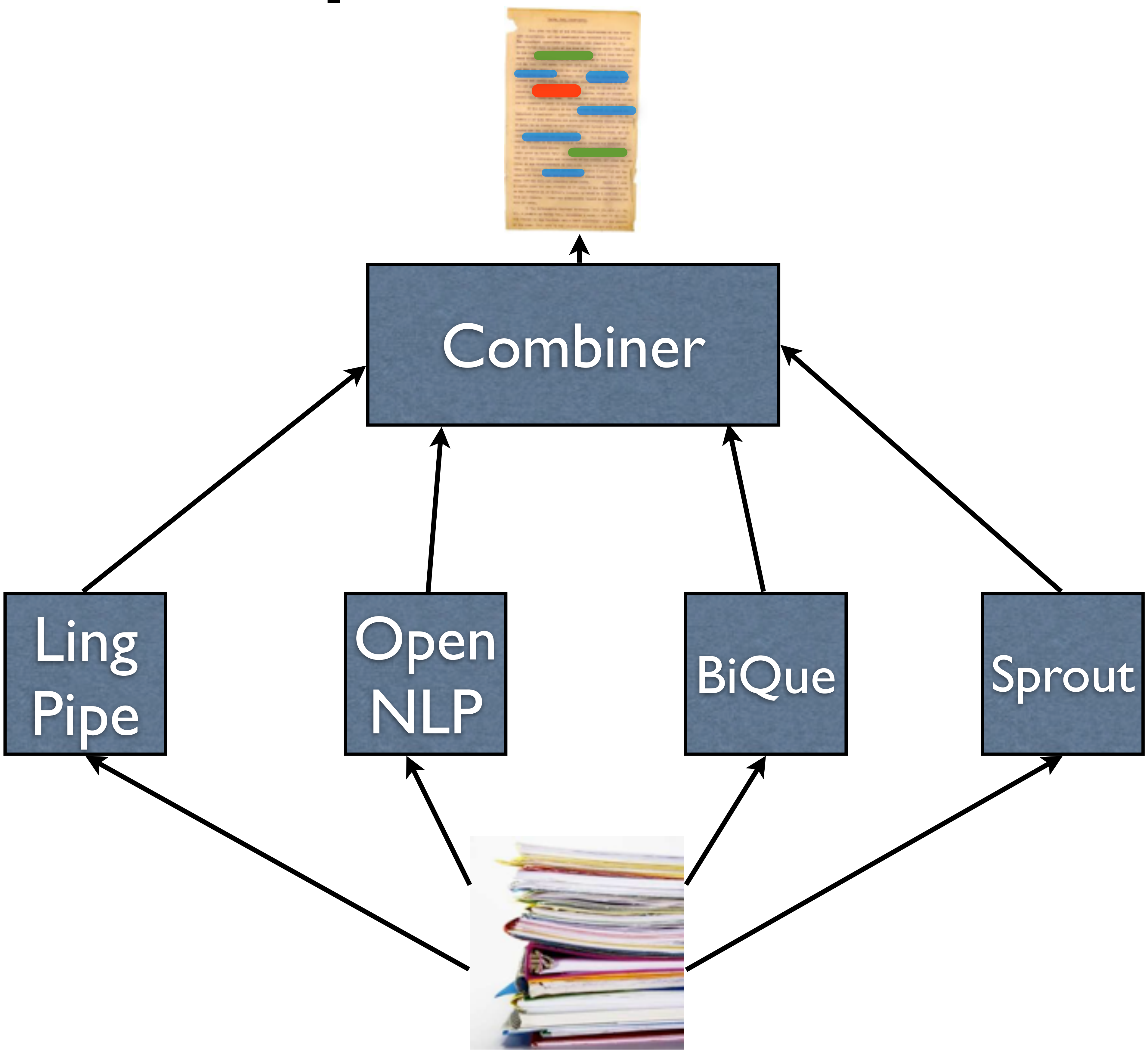


Example: NER



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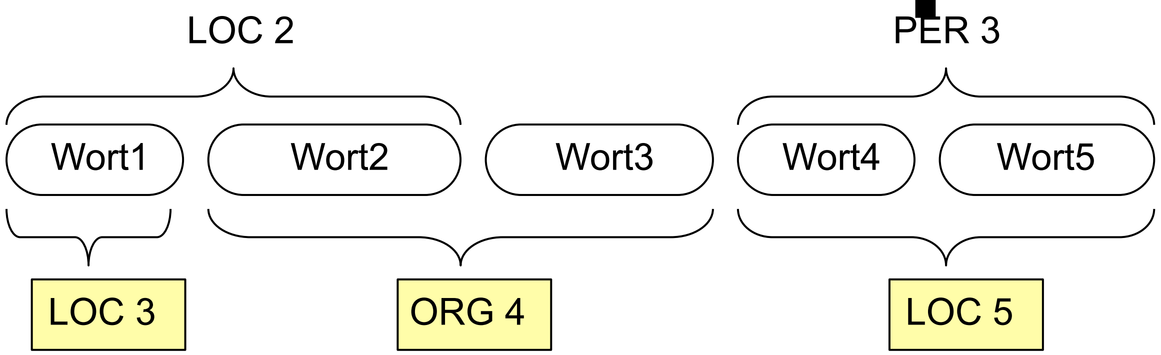
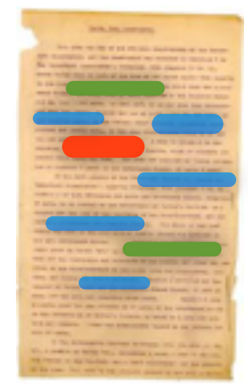
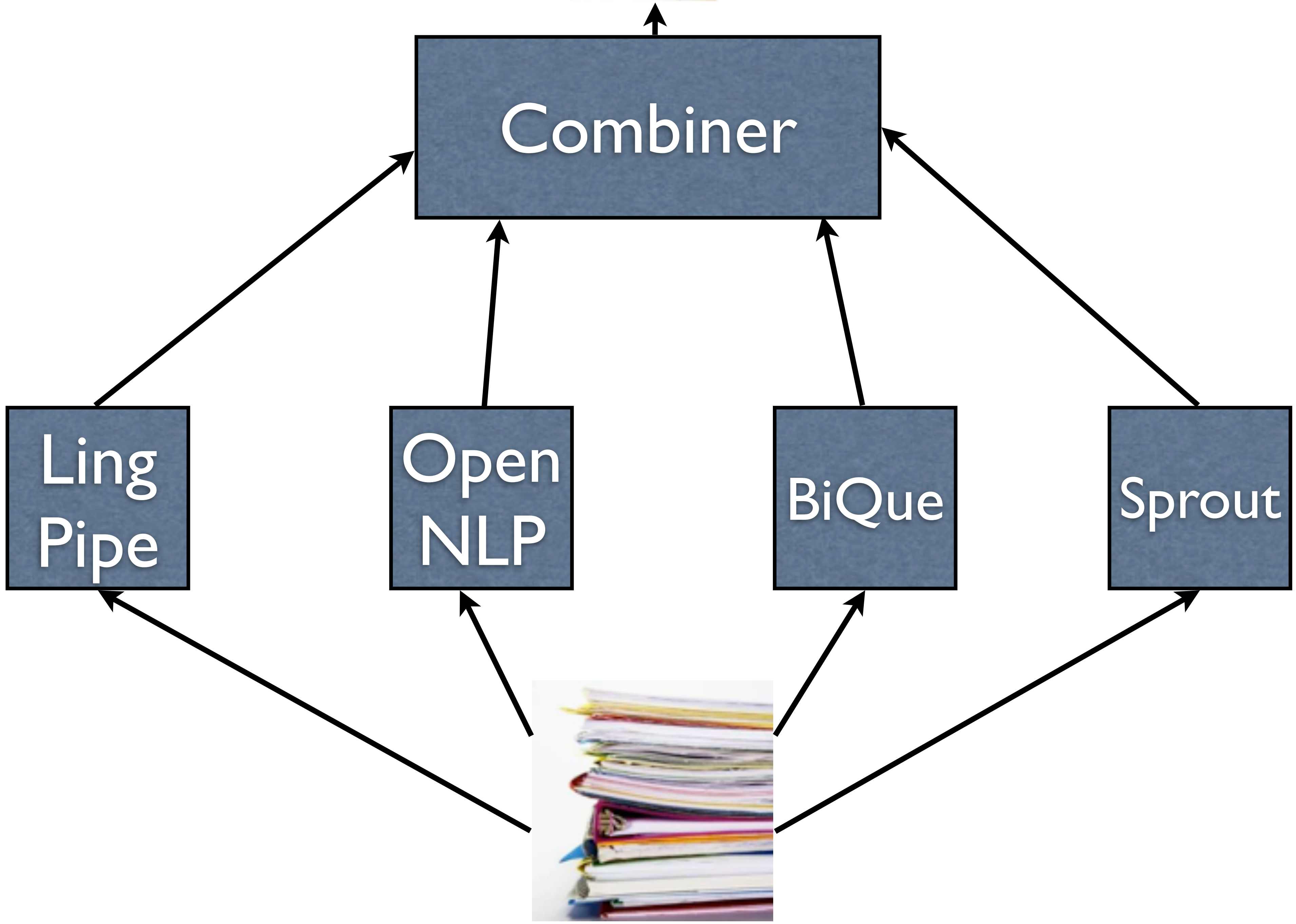


Problem:
- Ambiguities
- Bracketing





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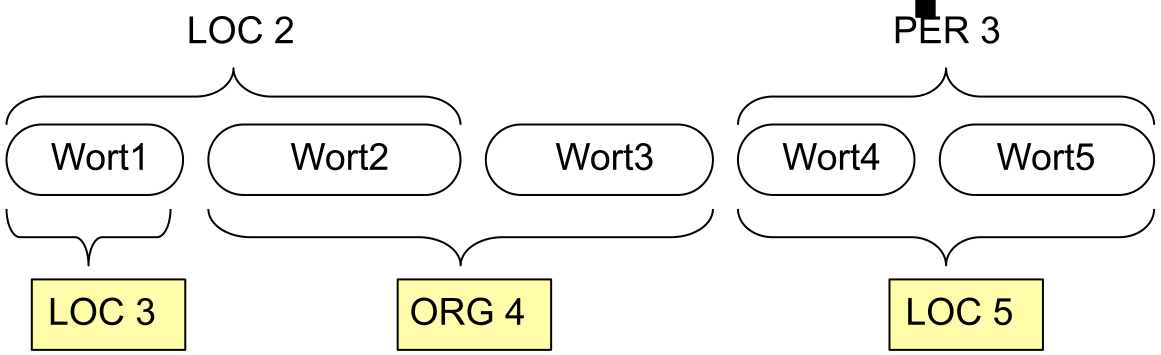

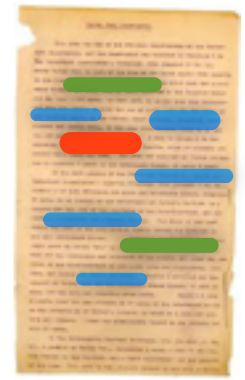

Solutions:
- meta-learning
- consider IE_i as independent black-boxes

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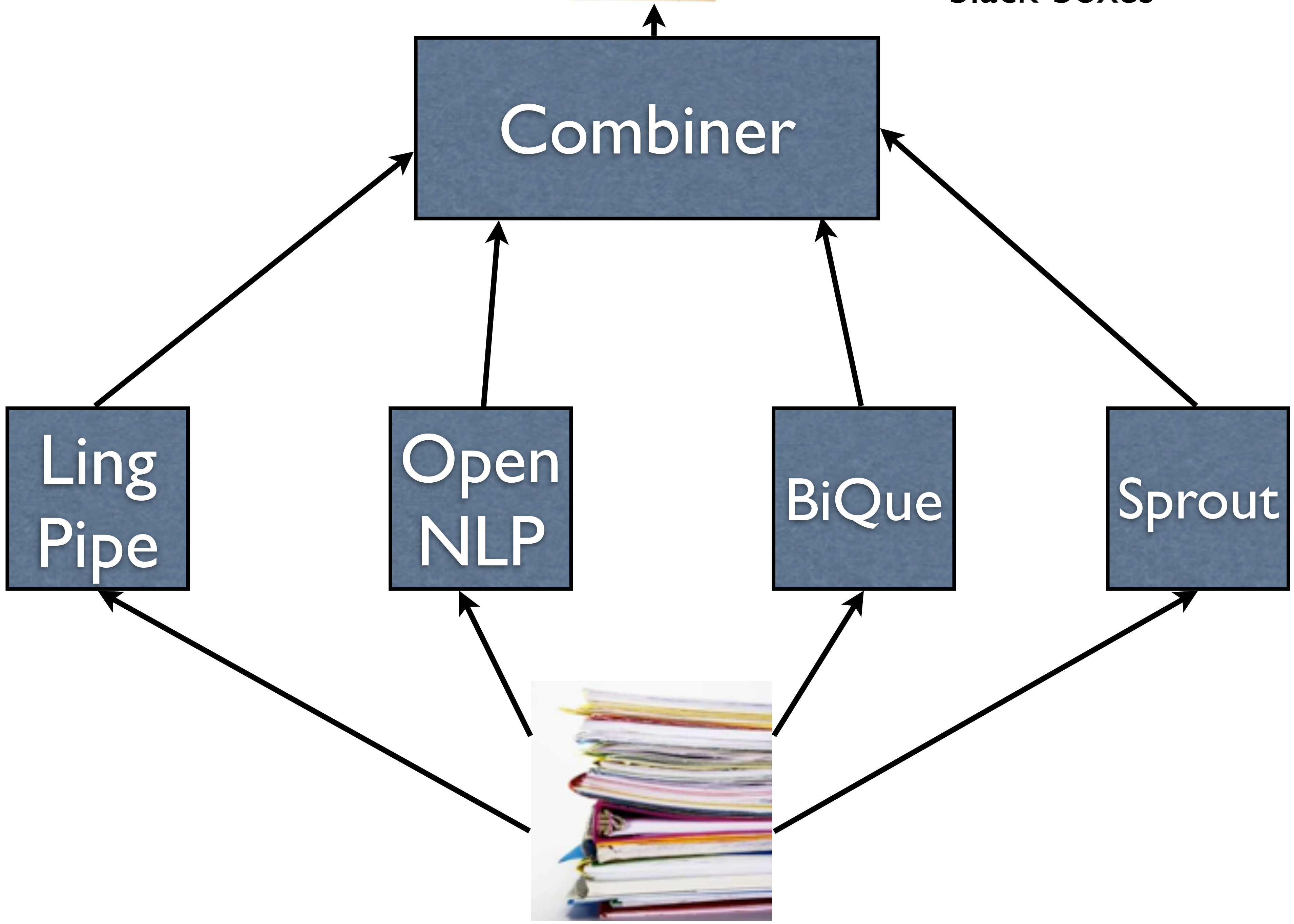

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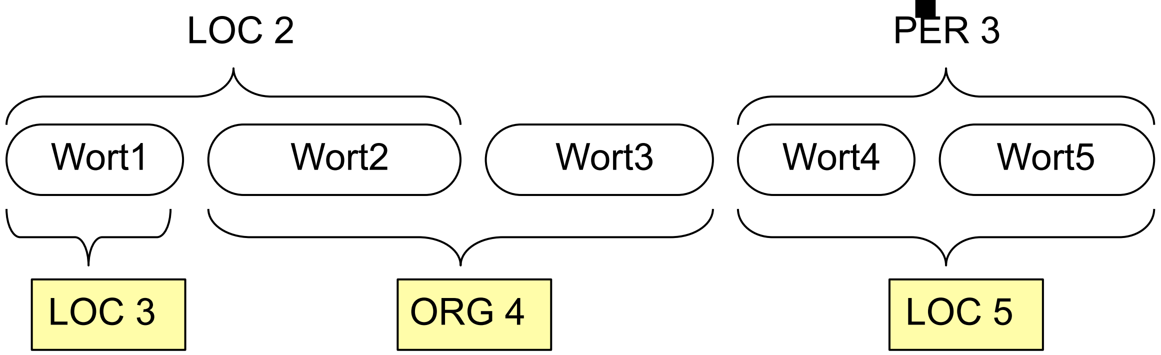

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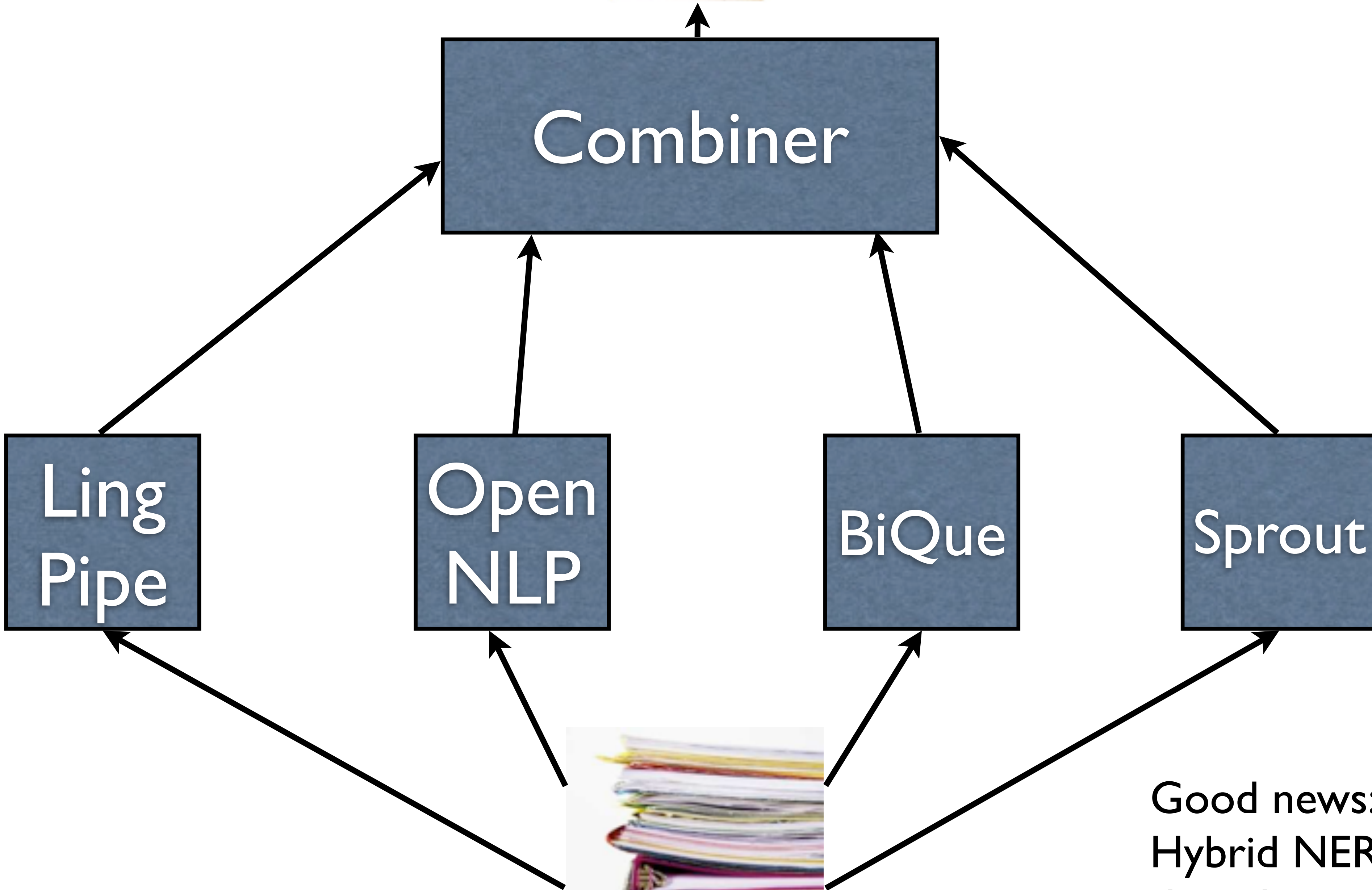

Good news:*
Hybrid NER are better than the single NER wrt. recall and precision.

Combining Information Extraction Systems Using Voting and Stacked Generalization
by: G Sigletos et al., J. Mach. Learn. Res., Vol. 6 (2005), pp. 1751-1782.

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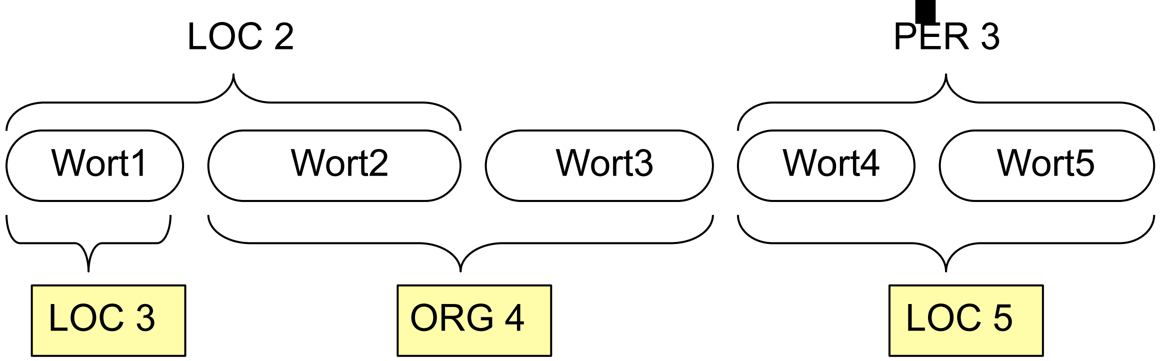

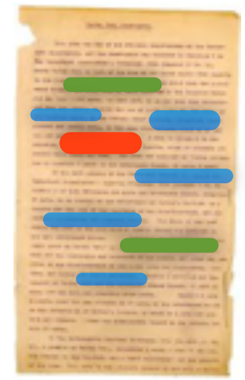

Meta learning
- majority voting
- stacking

Strategies:
- maximum weights
- linear regression: $P_C=1-\prod_i(1-P_i)$
- cross-validation

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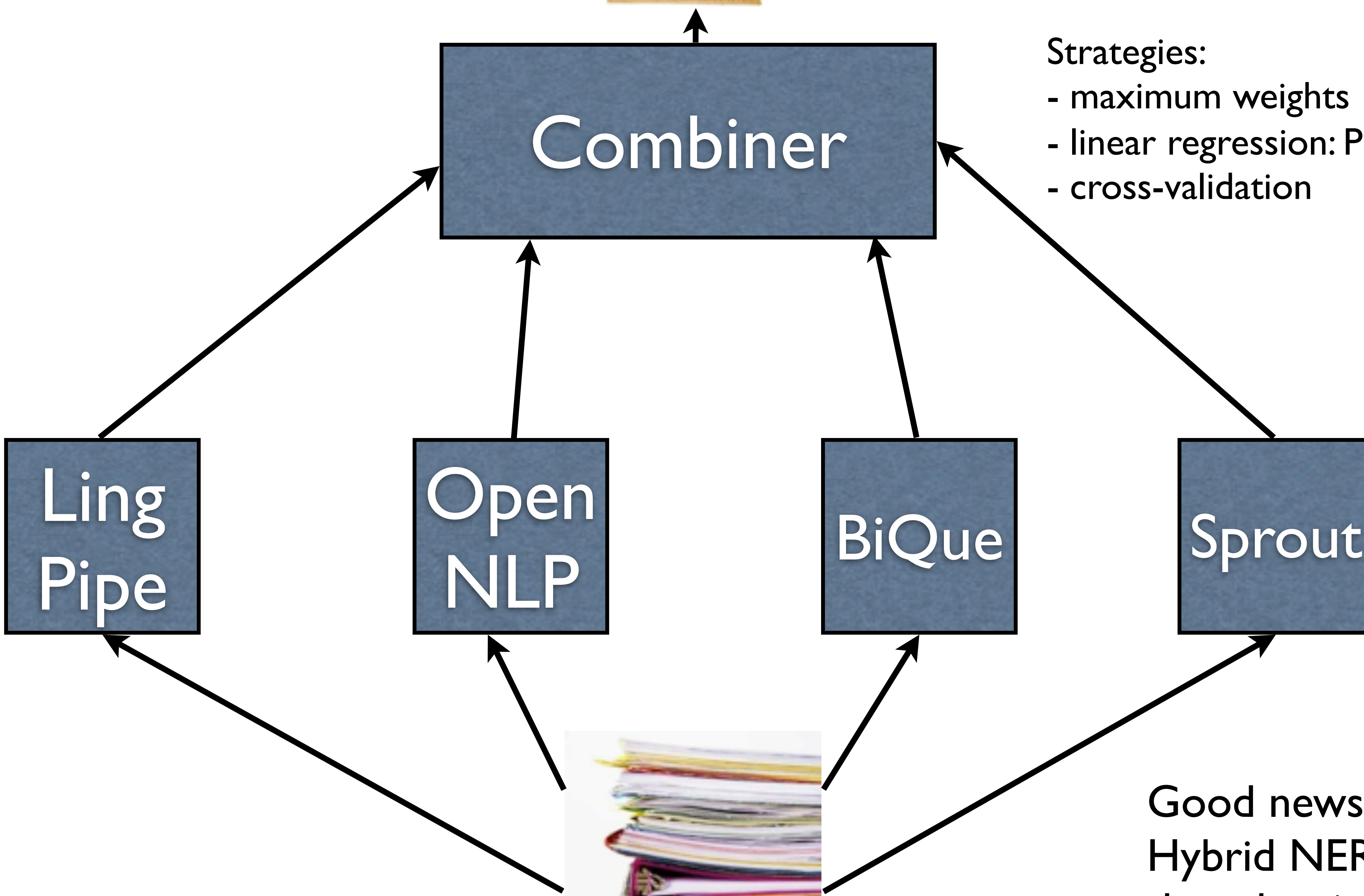

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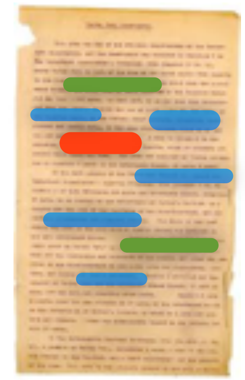
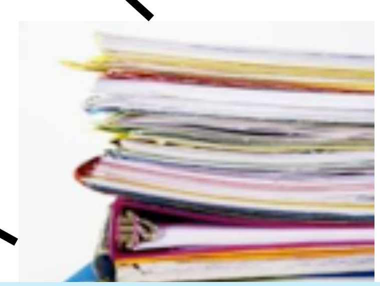


Corpus:
German press releases about turnover (Training: 4850 Tokens, Testing: 1000 Tokens)

Iterative Tag Insertion

MEM - Maximum Entropy Modeling

DOP - Data-Oriented Parsing



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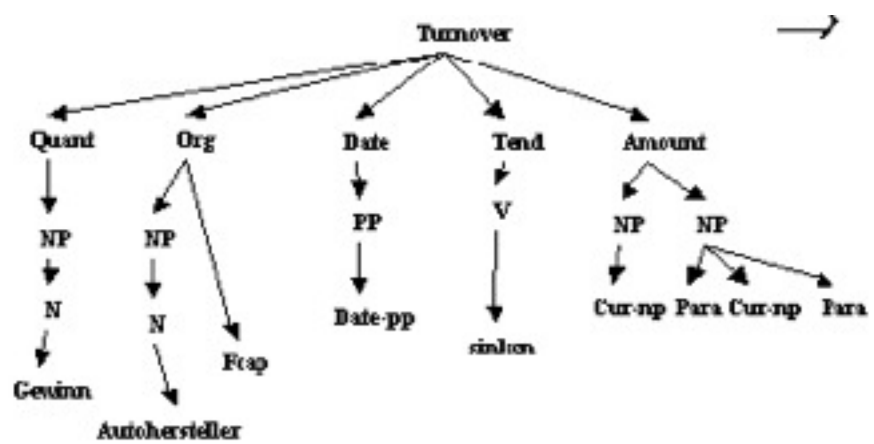

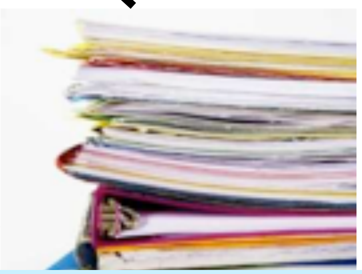

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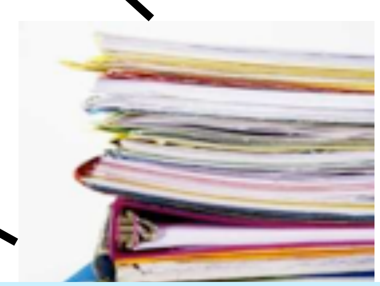
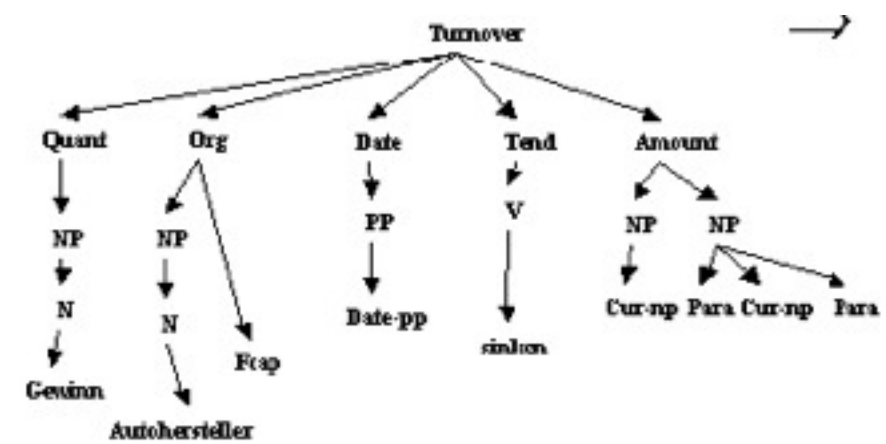


Result:
- only MEM: 79.3 %
- only DOP: 51.9 %
- both: 85.2 %



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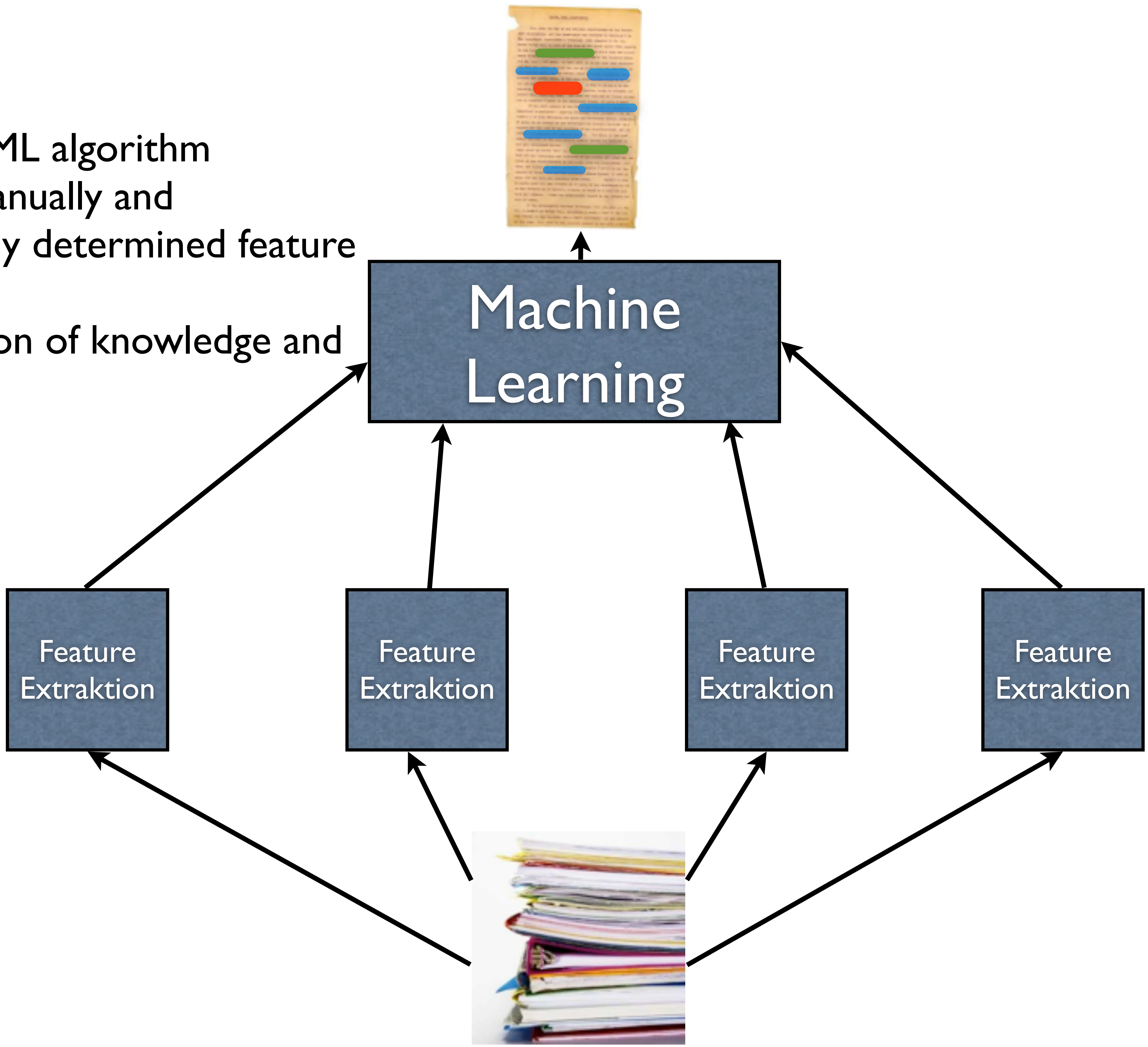
Feature based Strategies

Idea:
- choose a ML algorithm
- choose manually and automatically determined feature templates
- combination of knowledge and statistics



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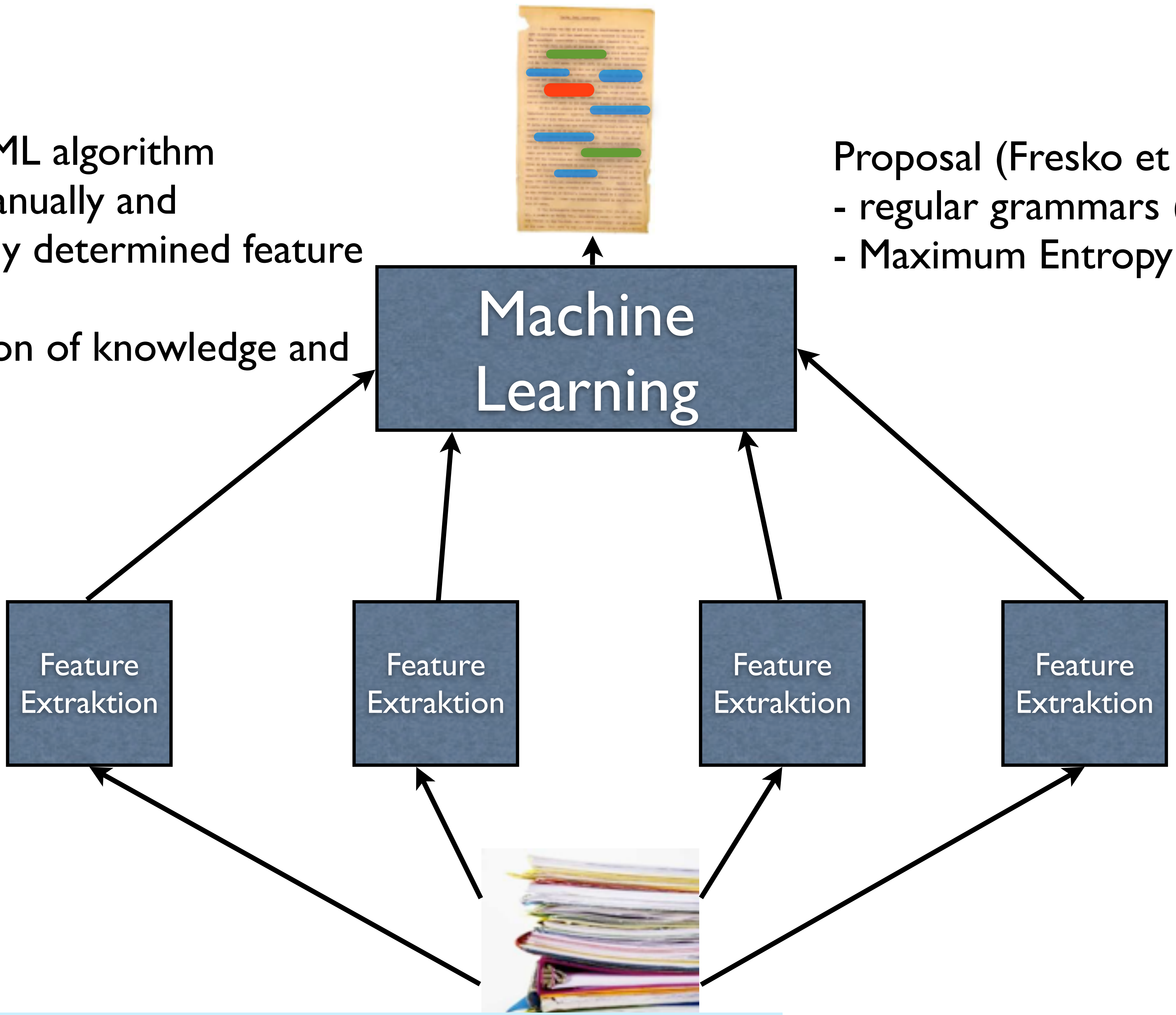

Proposal (Fresko et al., 2005):
- regular grammars (hand coded)
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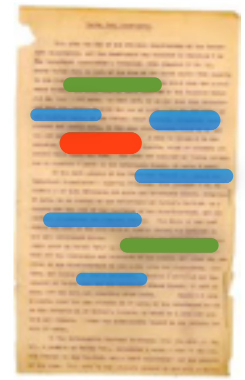

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Machine Learning

Feature Extraktion

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	Simple MERGE			MERGE+Rules		
	Rec.	Pre.	F.	Rec.	Pre.	F.
Org.	79.4	87.8	83.4	83.9	90.9	87.2
Per.	86.7	89.9	88.3	90.6	93.4	92.0
Loc.	85.9	85.3	85.6	91.5	91.8	91.7
All	82.7	87.3	**84.9**	87.9	91.7	**89.8**

Table 1. MUC7: After training with 100 documents.

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Co-Training & Bootstrapping

Bootstrapper

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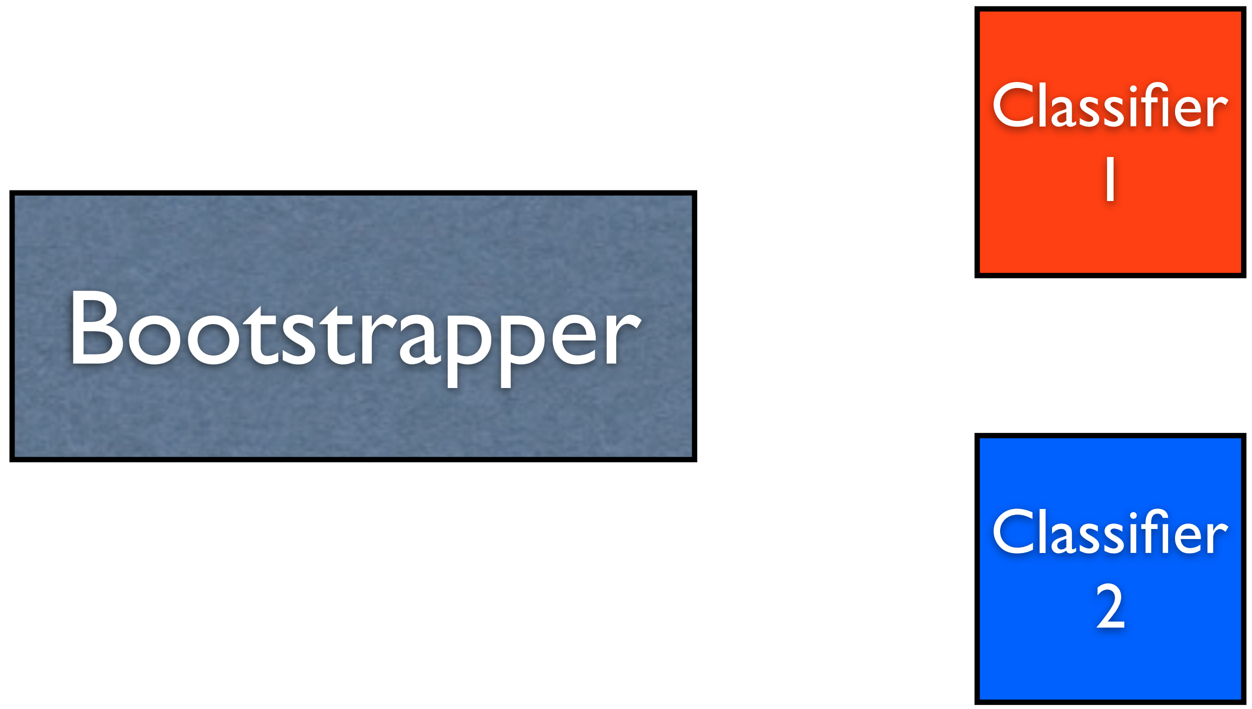

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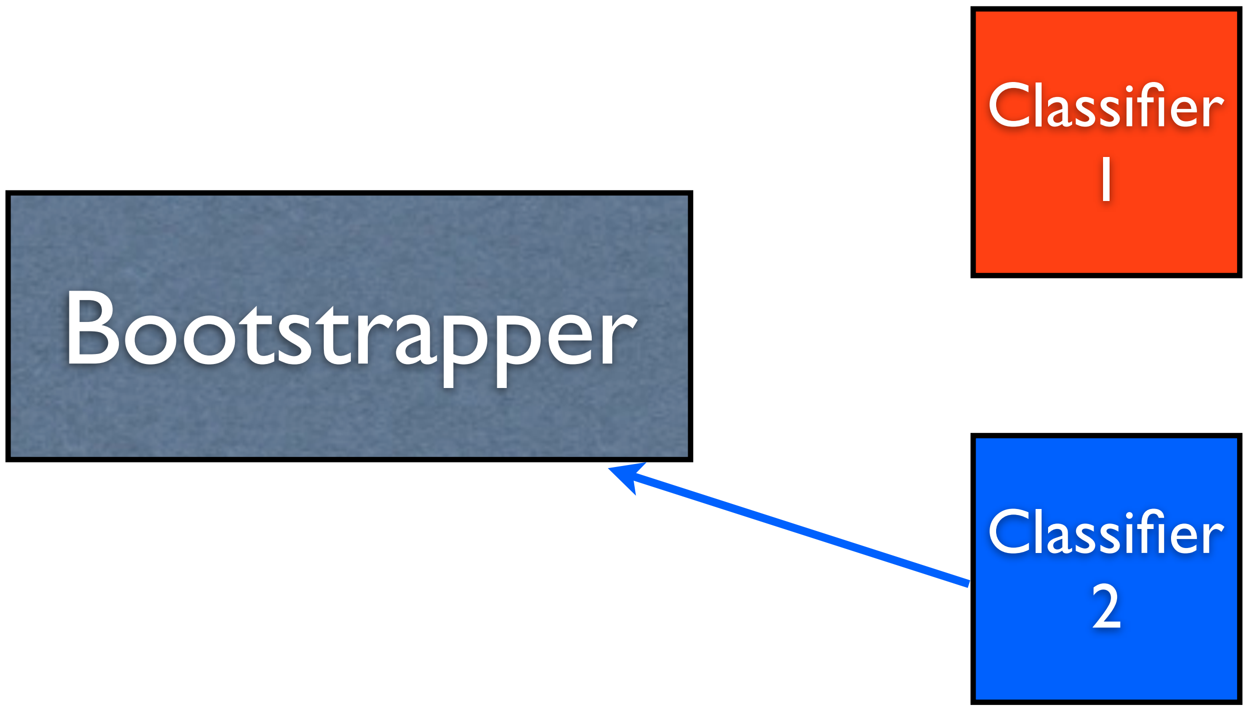

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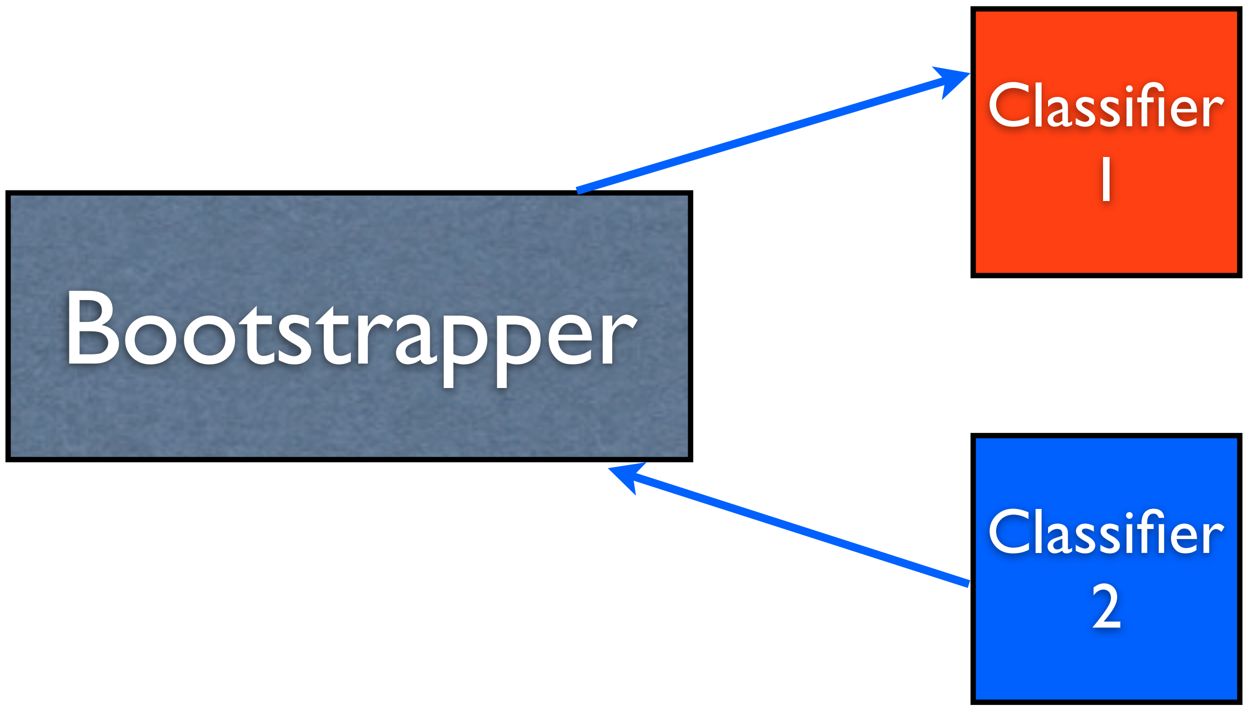

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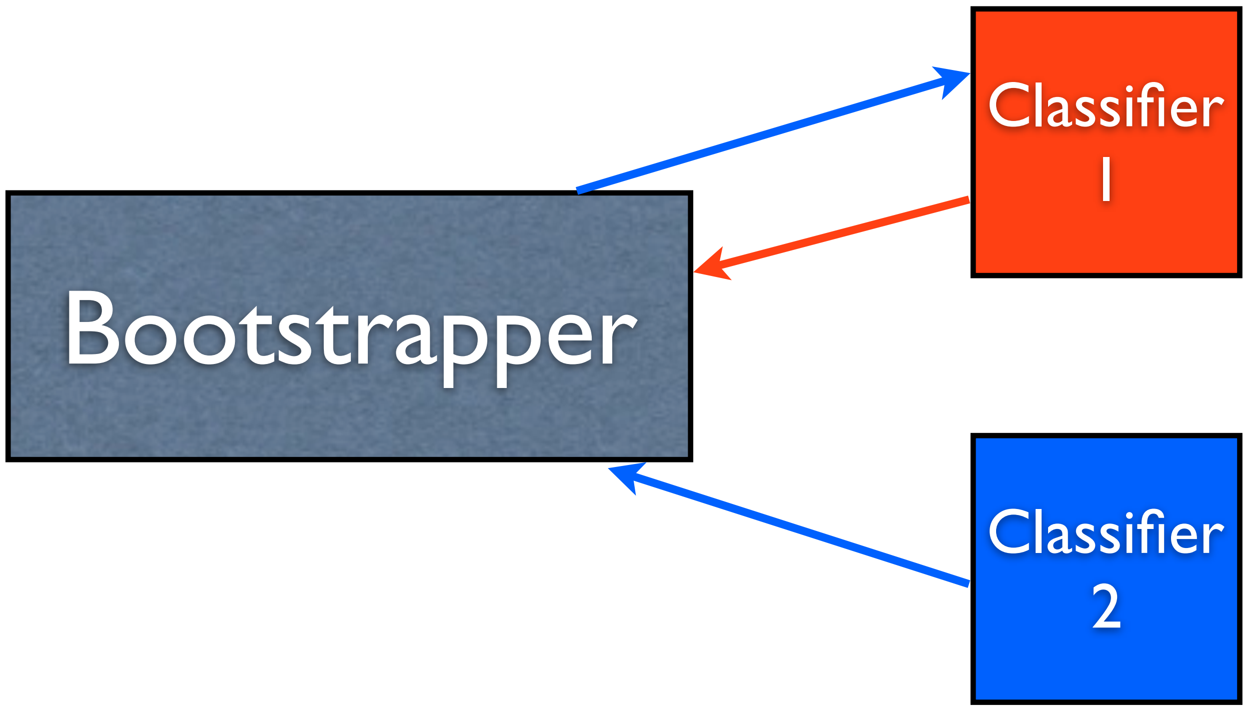

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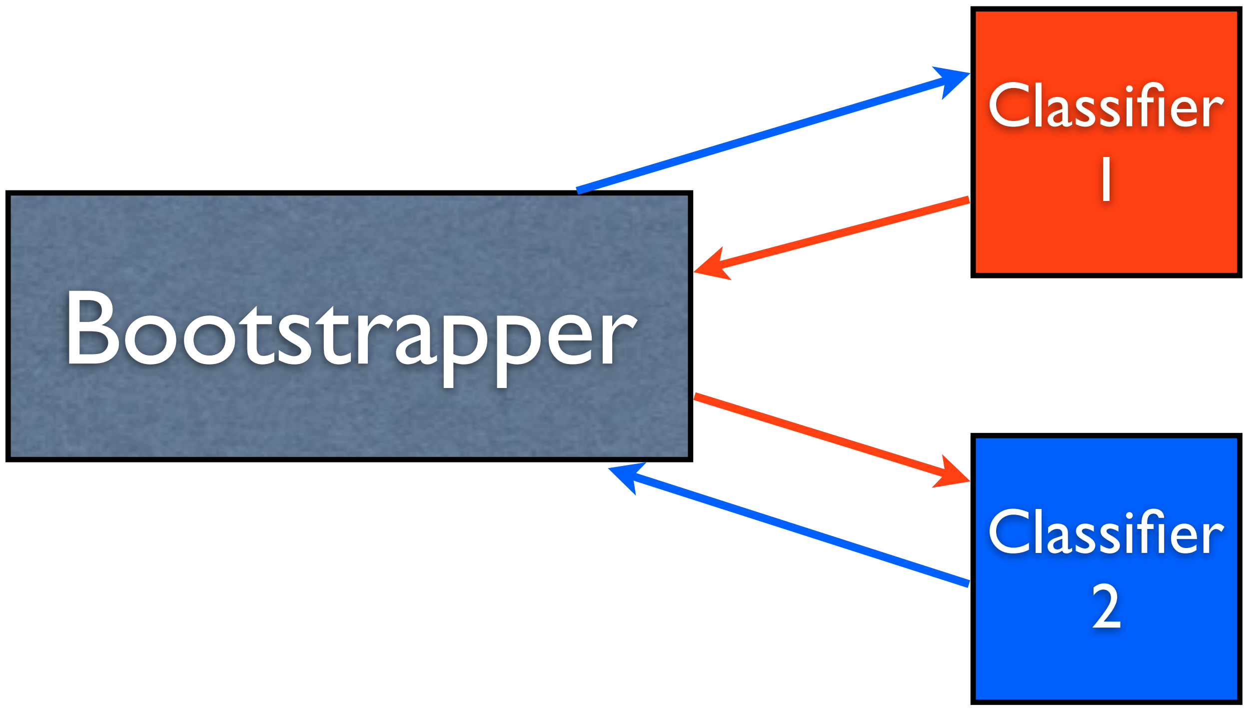

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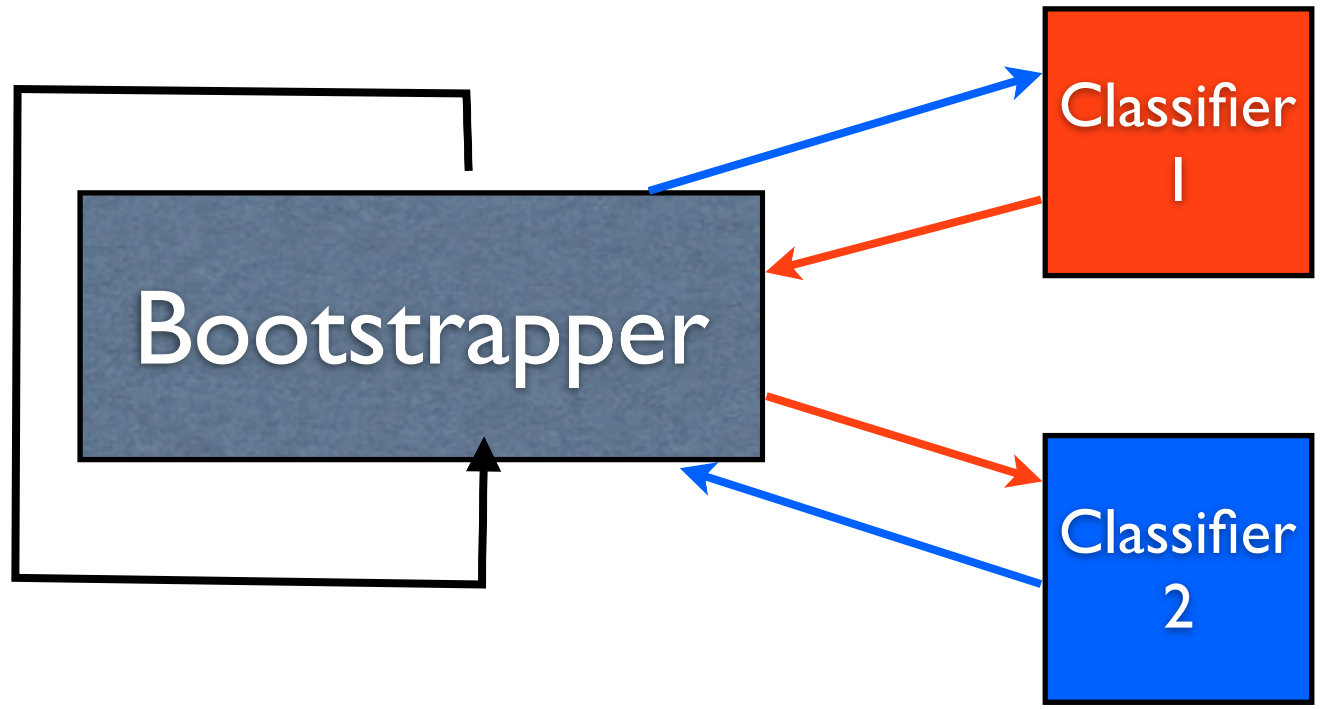

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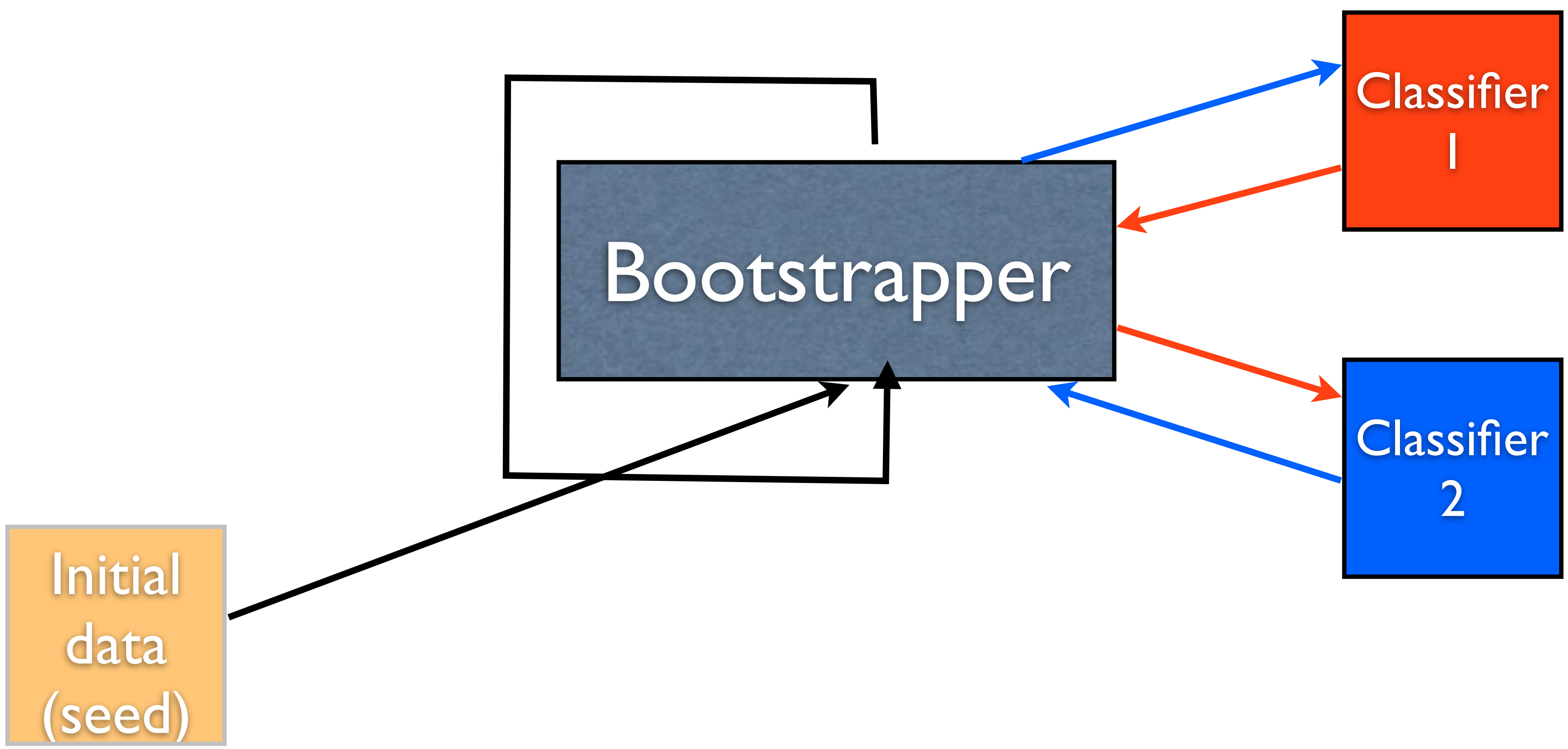
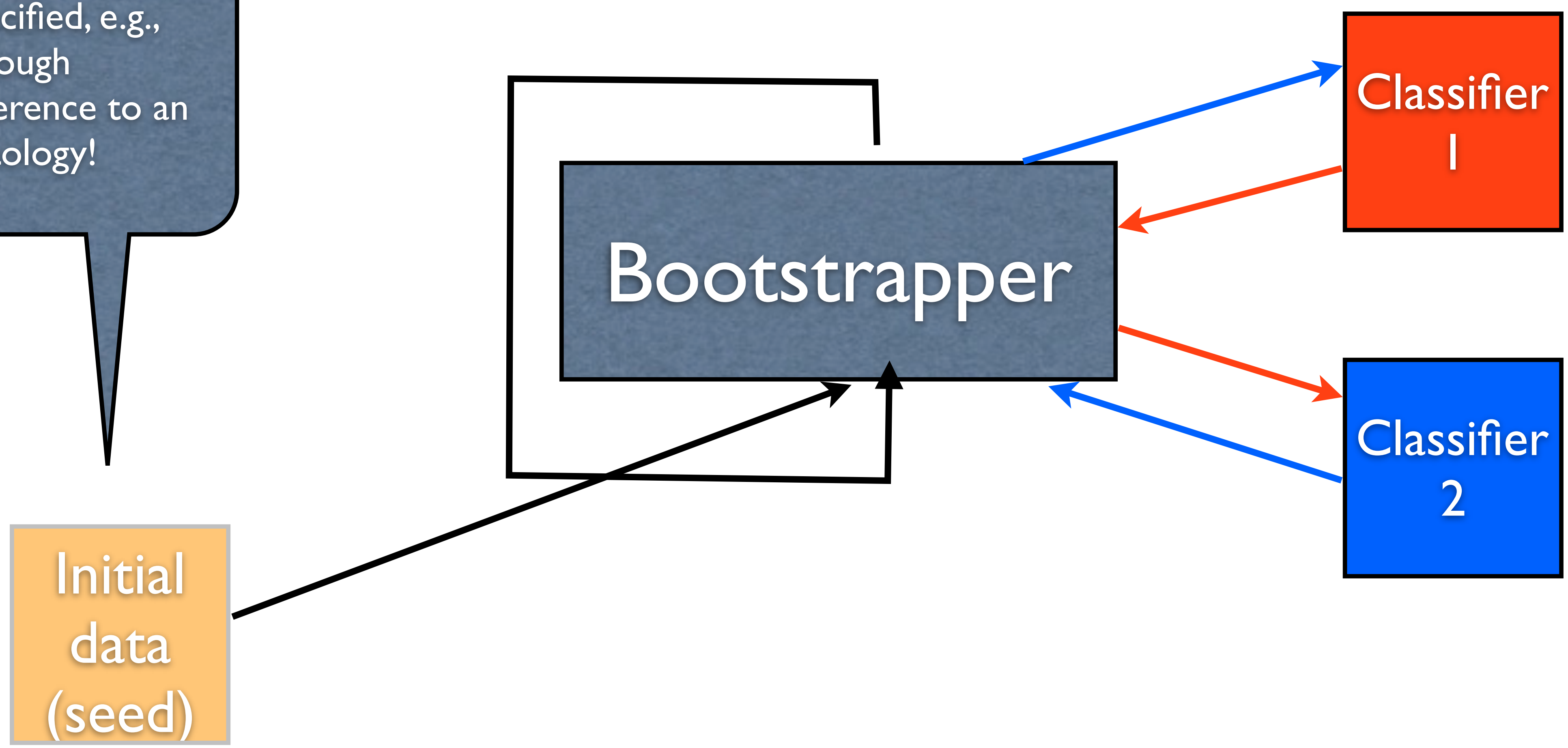


Co-Training & Bootstrapping

Note:
These are manually specified, e.g., through reference to an ontology!



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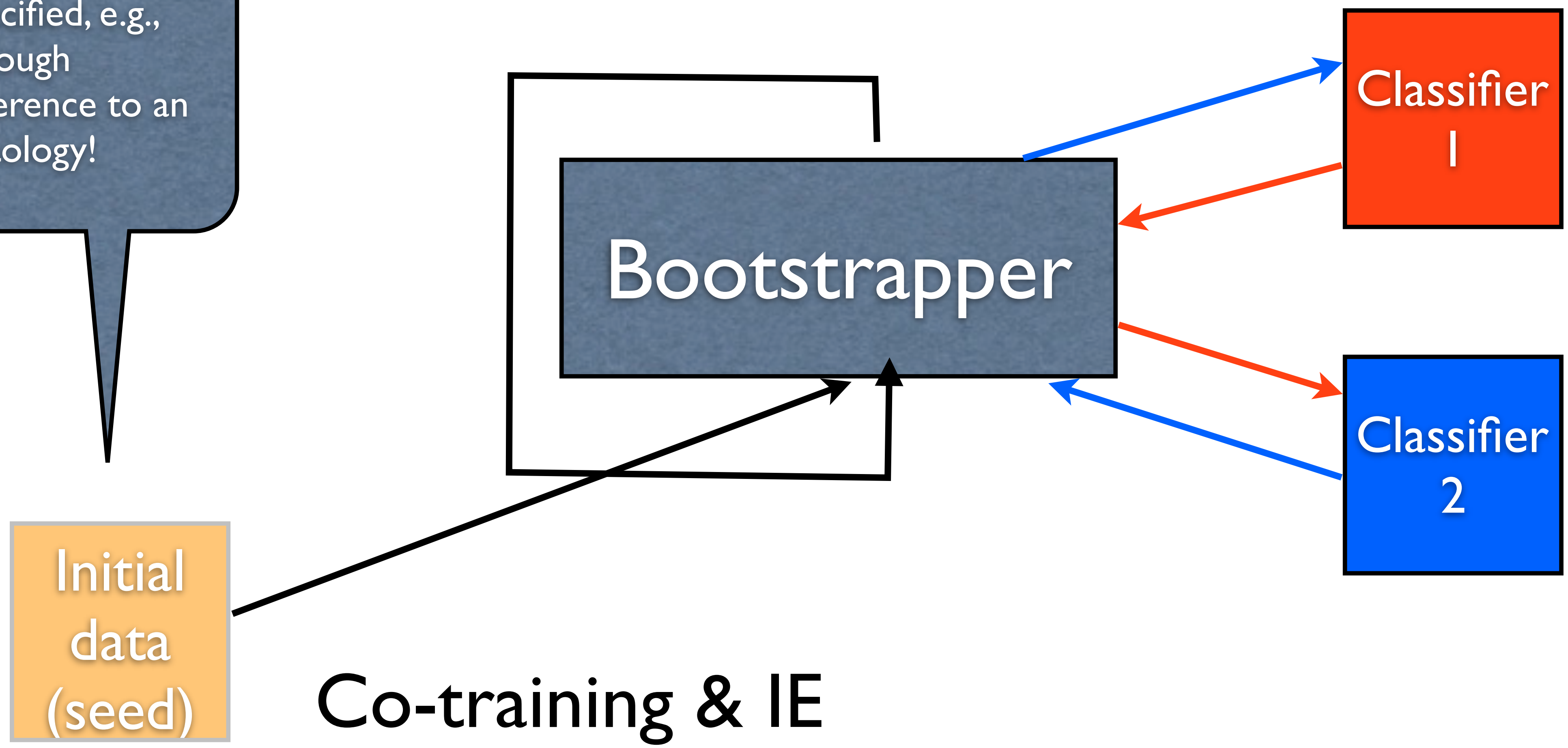


Co-training & IE

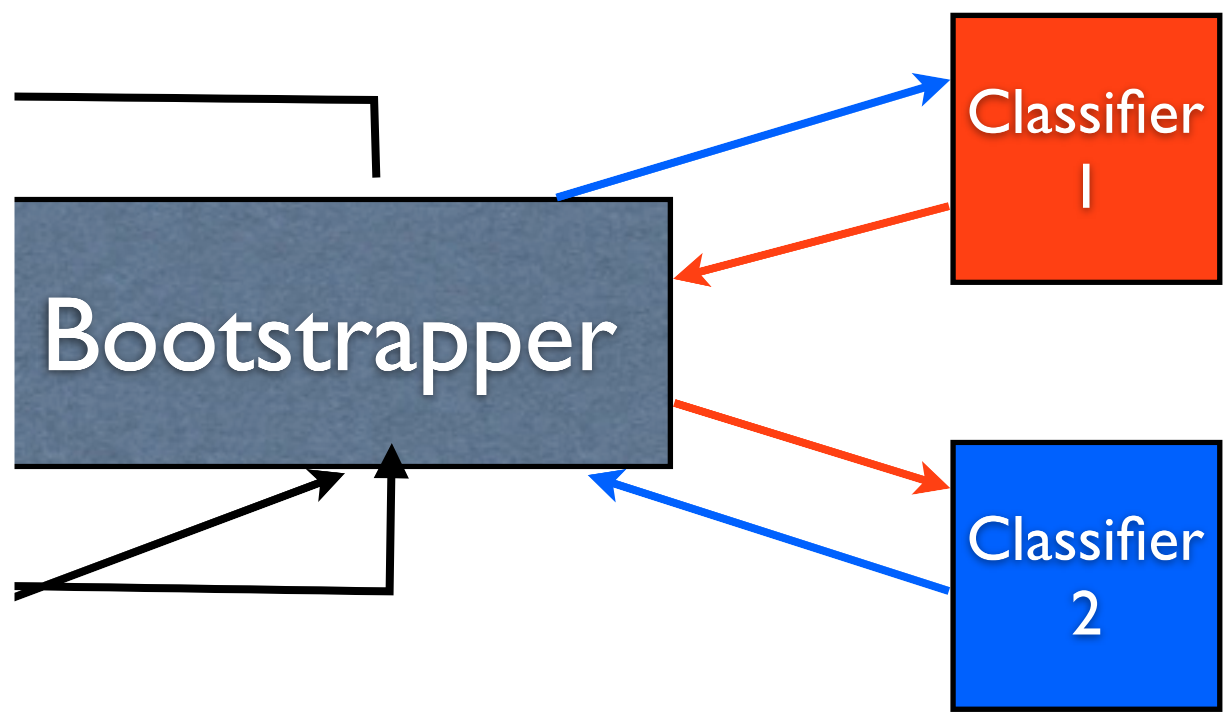
- NER, cf Singer & Collins, 1999
  Interaction of spelling and context features
- REE, cf. Surdeanu et al. 2006
  Interaction of text classifier and pattern acquisition

Co-Training & Bootstrapping

Note:
These are manually specified, e.g..

Baseline	Co-training
s(he) o(game)	**v(win) o(title)**
v(miss) o(game)	s(I) v(play)
v(play) o(game)	**s(he) v(game)**
v(play) io(in LOC)	s(we) v(play)
v(go) o(be)	**v(miss) o(game)**
s(he) v(be)	**s(he) v(coach)**
s(that) v(be)	**v(lose) o(game)**
s(I) v(be)	s(I) o(play)
s(it) v(go) o(be)	v(make) o(play)
s(it) v(be)	**v(play) io(in game)**
s(I) v(think)	v(want) o(play)
s(I) v(know)	**v(win) o(MISC)**
s(I) v(want)	**s(he) o(player)**
s(there) v(be)	**v(start) o(game)**
s(we) v(do)	s(PER) o(contract)
v(do) o(it)	s(we) o(play)
s(it) o(be)	**s(team) v(win)**
s(we) v(are)	**v(rush) io(for yard)**
s(we) v(go)	**s(we) o(team)**
s(PER) o(DATE)	**v(win) o(Bowl)**

Table 4: Top 20 patterns acquired from the Sports domain by the baseline system (Riloff) and the co-training system for the AP collection. The correct patterns are in bold.



ing & IE

f Singer & Collins, 1999

Interaction of spelling and context features

- REE, cf. Surdeanu et al. 2006

Interaction of text classifier and pattern acquisition

QA and Hybrid IE

- Observation: answer extraction is a kind of question-driven IE (NER and REE)

Where does Bill Gates live?	lives_in(Town:?, Pers:Bill Gates)
What is a CEO?	is_a(Pos:CEO,Conc:?)

Figueroa, A., Neumann, G. and Atkinson, J. (2009) Searching for Definitional Answers on the Web using Surface Patterns. In journal IEEE Computer volume 42 number 4, Pages 68-76, IEEE, 4/2009.

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Domain open answering of definition questions from the Web

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Domain open answering of definition questions from the Web

Was ist XYZ ?

XYZ is a
XYZ is a
XYZ is a
XYZ is a
XYZ is a
XYZ is a
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Domain open answering of definition questions from the Web

Problem:
How to find optimal ranking of answer candidates?

Figueroa, A., Neumann, G. and Atkinson, J. (2009) Searching for Definitional Answers on the Web using Surface Patterns. In journal IEEE Computer volume 42 number 4, Pages 68-76, IEEE, 4/2009.

Wikipedia as Blueprint!

- Learn from Wikipedia, what a good verbalization of a definition looks like!

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Solution:
Rank answer candidates according to similarity of Wikipedia?

Wikipedia as Blueprint!

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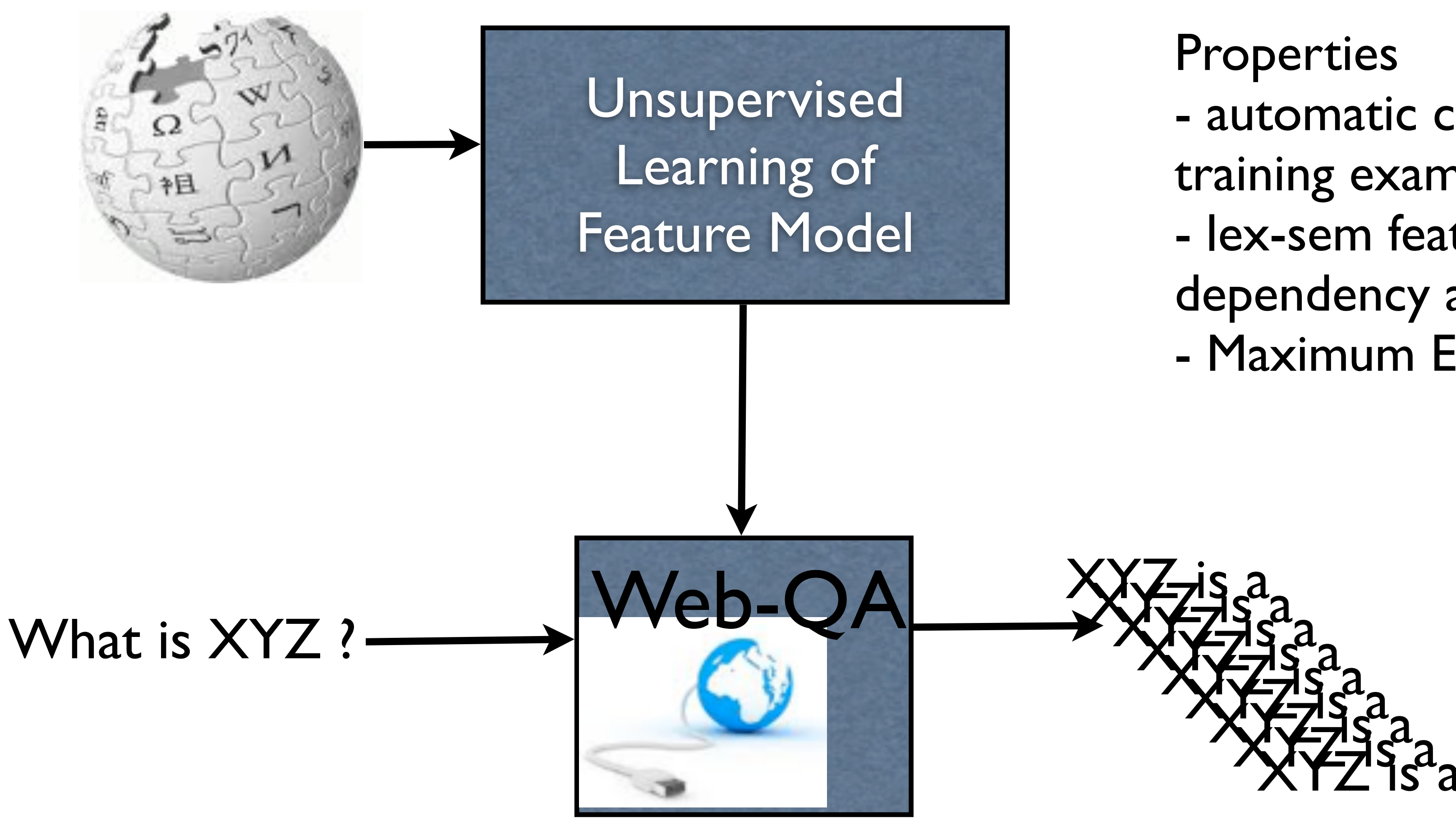

Properties
- automatic computation of POS und NEG training examples
- lex-sem feature-templates via dependency analysis
- Maximum Entropy Modeling

Solution:
Rank answer candidates according to similarity of Wikipedia?

Wikipedia as Blueprint!

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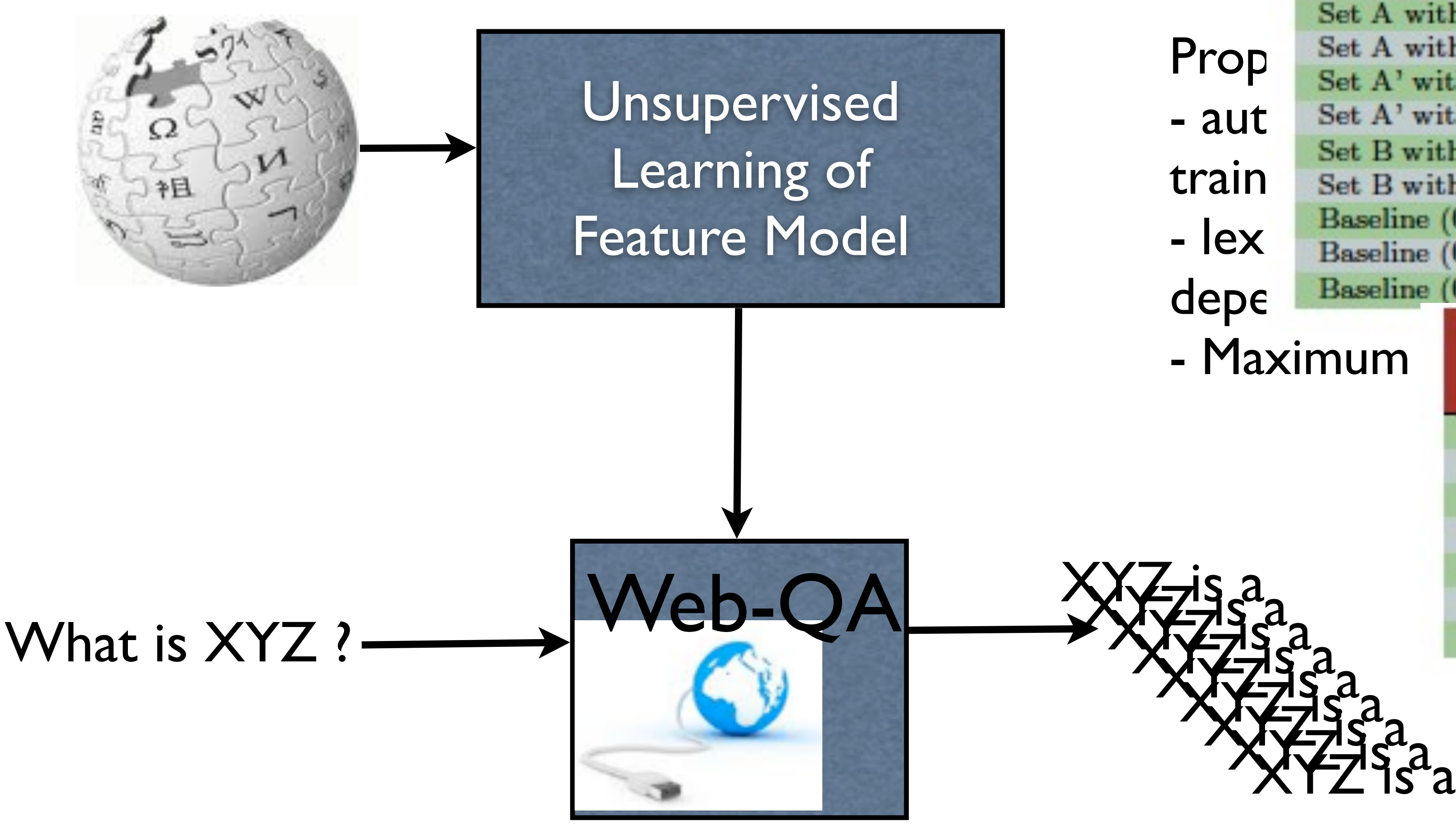

Prop
- aut
train
- lex
depe
- Maximum

Best Attributes Found for	Applied to Set A' Accuracy	Applied to Set A Accuracy
Set A without NLP	81.16%	
Set A with NLP	**85.94%**	
Set A' without NLP		78.28%
Set A' with NLP		**83.04%**
Set B without NLP	76.86%	75.50%
Set B with NLP	63.19%	74.61%
Baseline (0.3)	54.13%	44.17%
Baseline (0.2)	54.63%	44.23%
Baseline (0.1)	56.25%	44.77%

Best Attributes Found for	Applied to Set B Accuracy
Set A without NLP	**59.86%**
Set A with NLP	58.71%
Set A' without NLP	58.25%
Set A' with NLP	58.44%
Baseline (0.3)	56.26%
Baseline (0.2)	57.77%
Baseline (0.1)	56.73%

according to similarity of
Wikipedia?

Wikipedia as Blueprint!

- Learn from Wikipedia, what a good verbalization of a definition looks like!

Unsupervised Learning of Feature Model

What is XYZ ?

Web-QA

XYZ is a
XYZ is a
XYZ is a
XYZ is a
XYZ is a
XYZ is a
XYZ is a
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Prop
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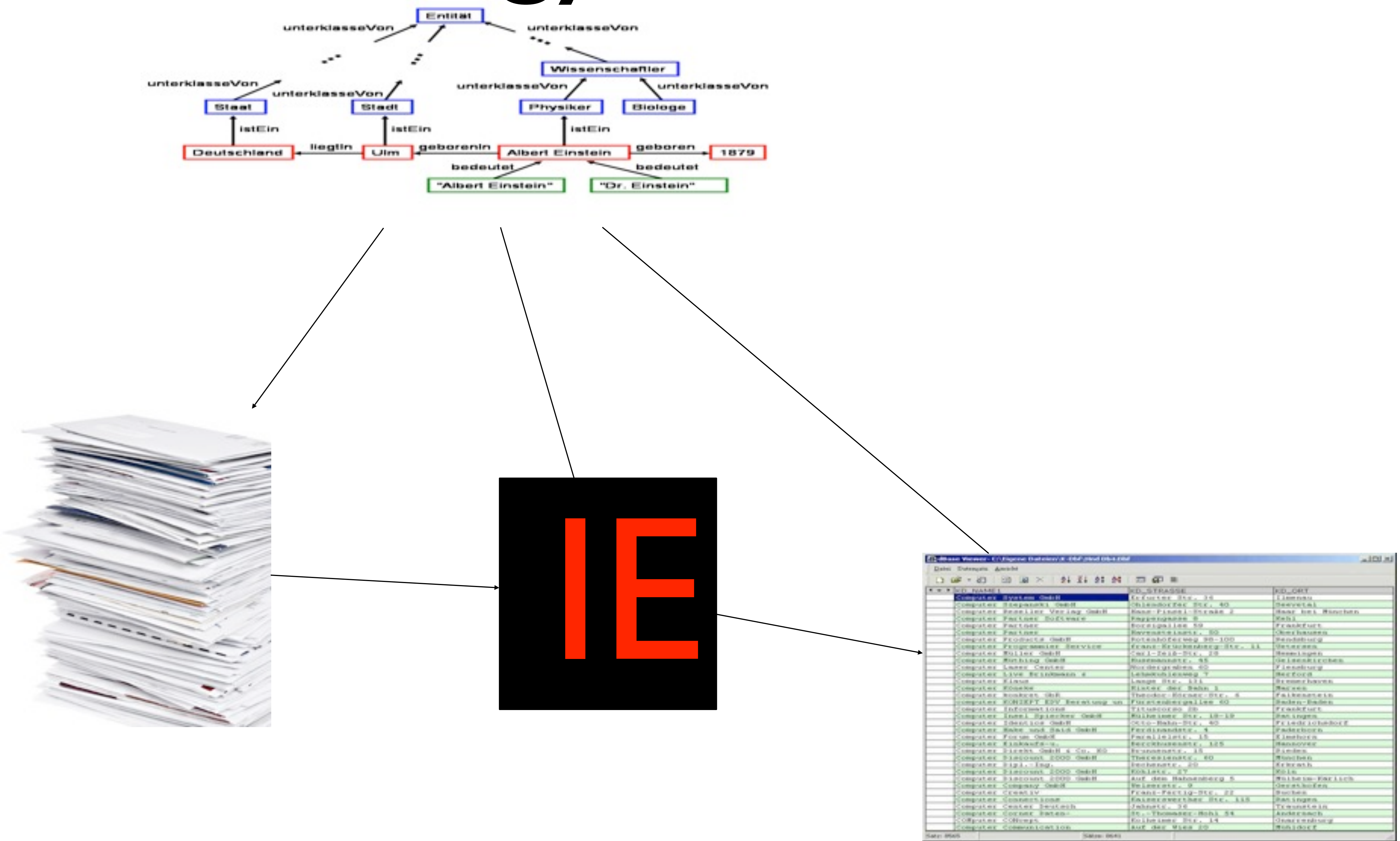
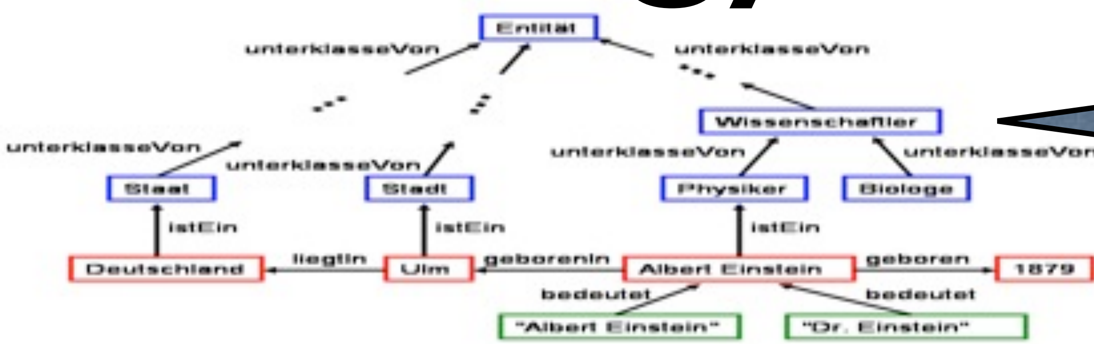
Remark: Method is a step towards Web-scalable ontology learning.

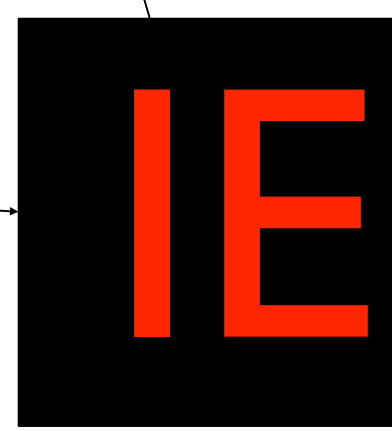
Ontology based IE

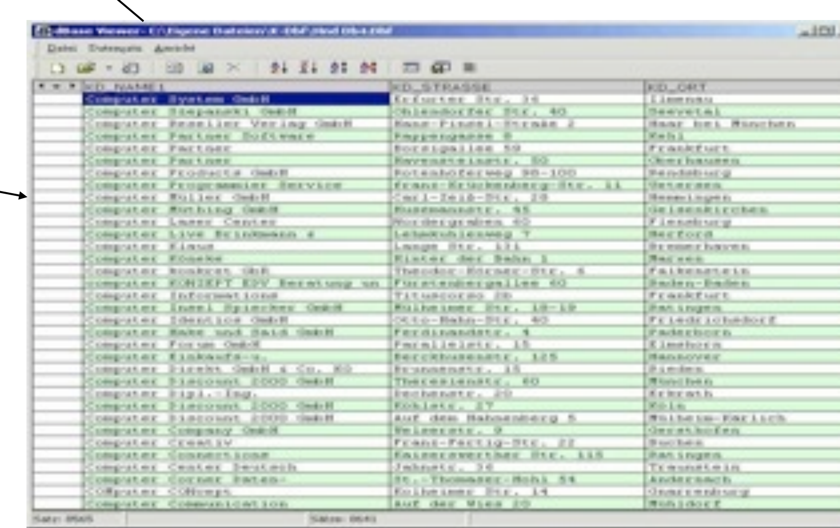


Ontology based IE



The ontology defines the type of the information, which has to be extracted from texts: e.g., types of or institutions and their inter relationship. It defines the structure of the data base, which has to be extracted automatically with the help of OBIE.





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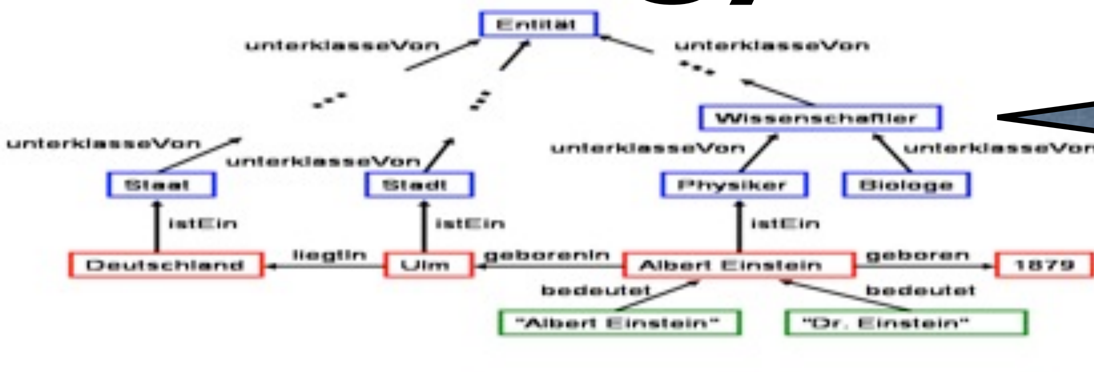

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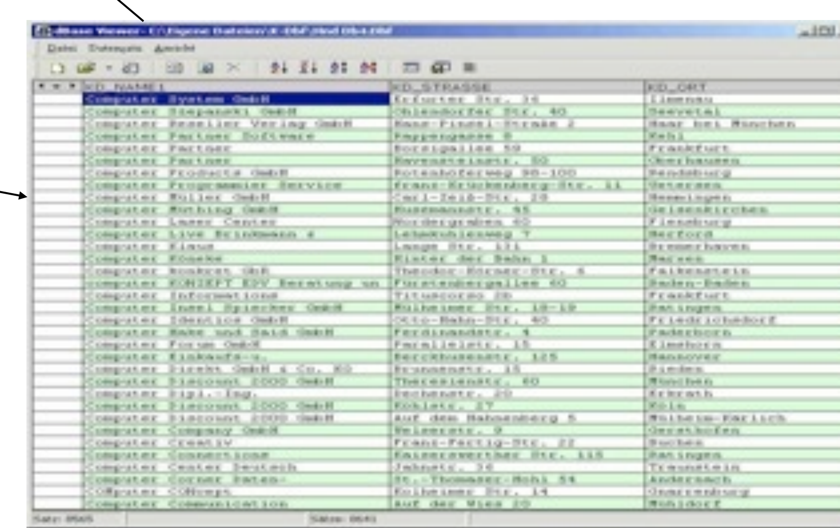
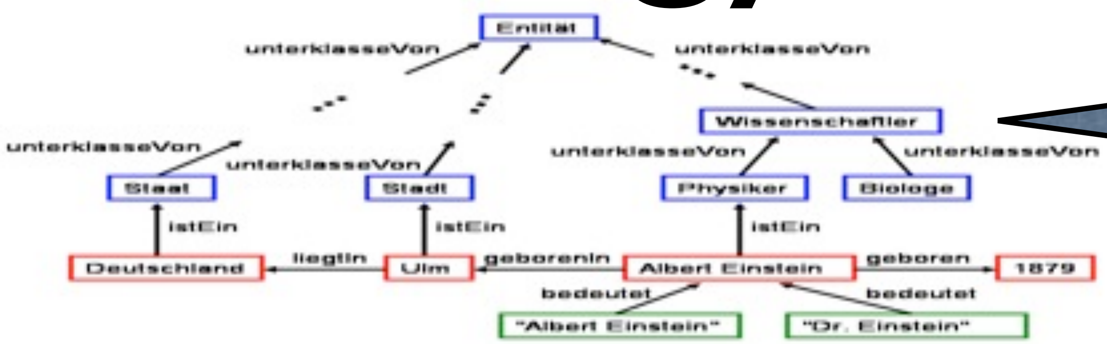


Ontology population
ontology learning

Ontology based IE



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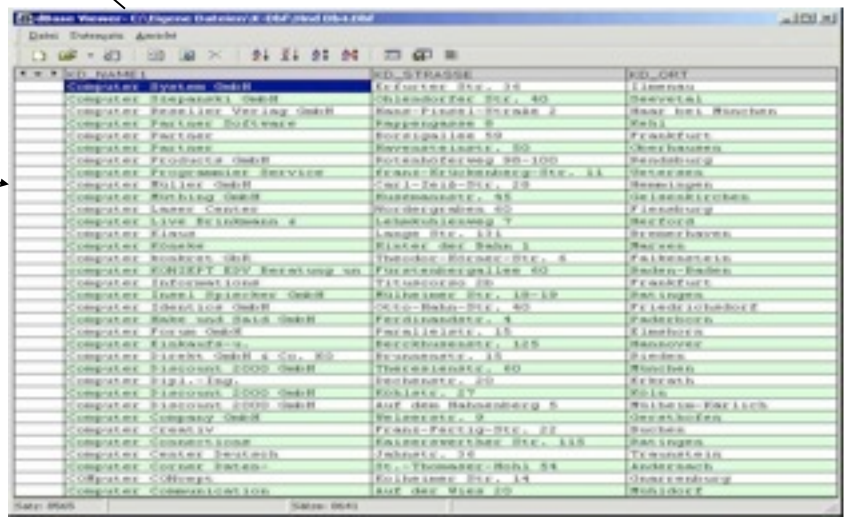
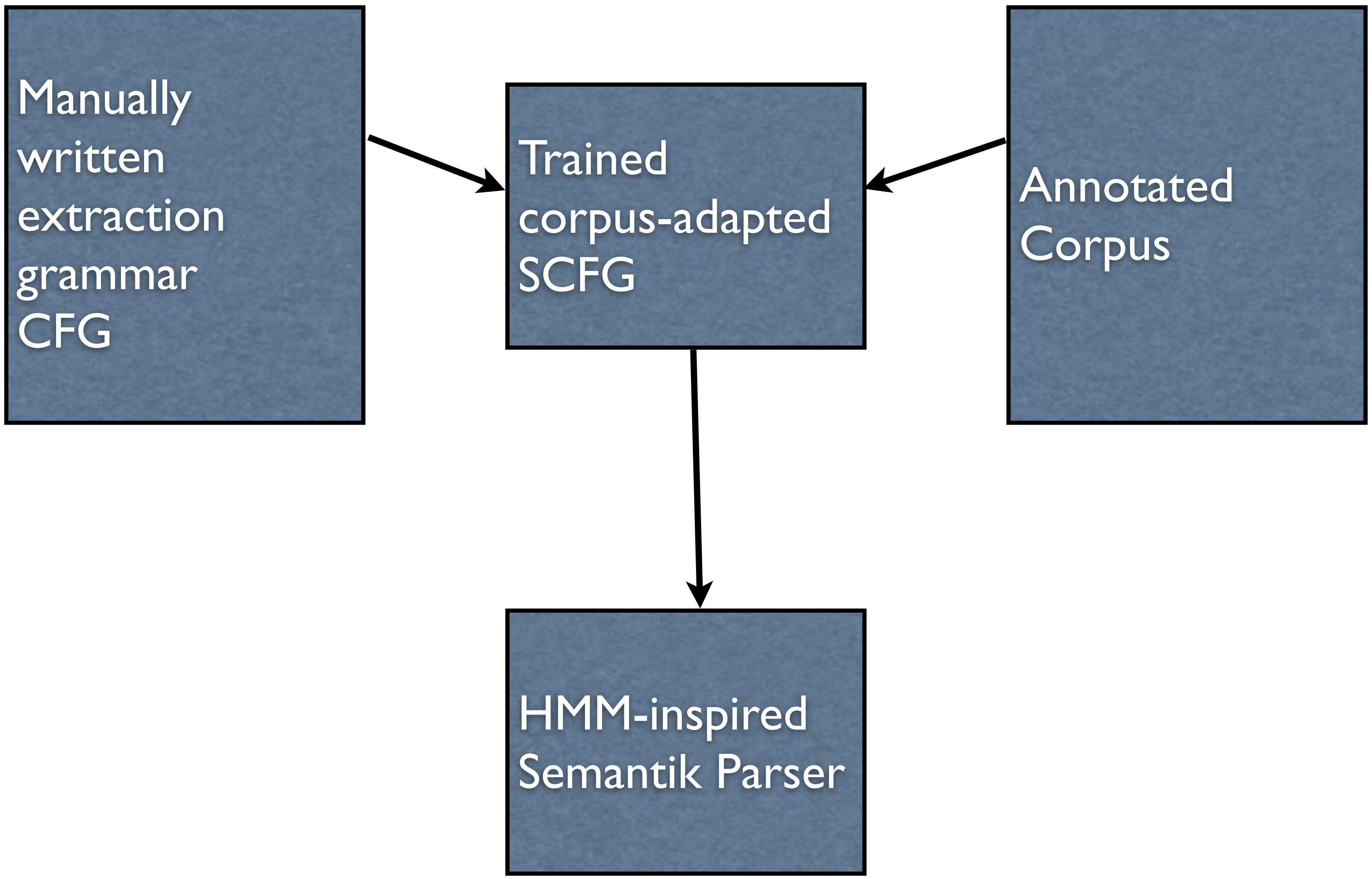


Ontology population ontology learning

Projekt TheseusOrdo TechWatch

TEG - Tree Extraction Grammars



Rosenfeld, Feldman & Freski „TEG - a hybrid approach to information extraction“, Knowledge Information Systems (2006) 1-18.

TEG - Example

Hand coded grammars

```
nonterm start Text;
concept Person;
ngram NGFirstName;
ngram NGLastName;
ngram NGNone;
termlist TLHonorific = Mr Mrs Miss Ms Dr;
(1) Person :- TLHonorific NGLastName;
(2) Person :- NGFirstName NGLastName;
(3) Text :- NGNone Text;
(4) Text :- Person Text;
(5) Text :- ;
```

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Collect statistics

P(Dr | **TLHonorific***)* = 1⁄5 (choice of one term among five equiprobable ones),
P(Dr | **NGFirstName***)* ≈ 1/*N*, where *N* is the number of all known words (untrained ngram behaviour).

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termlist TLHonorific = Mr Mrs Miss Ms <2>Dr;
Person :- <2>TLHonorific NGLastName;
Text :- <11>NGNone Text;
Text :- <2>Person Text;
Text :- <2>;

adapt rules

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Parse corpus

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TEG - Experiments

MUC-7 NER task

	HMM entity extractor			Emulation using TEG			DIAL Rules			Full TEG system		
	R	P	F1	R	P	F1	R	P	F1	R	P	F1
Person	86.91	85.13	86.01	86.31	86.83	86.57	81.32	93.75	87.53	93.75	90.78	92.24
Org	87.94	89.75	88.84	85.94	89.53	87.7	82.74	93.36	88.05	89.49	90.9	90.19
Location	86.12	87.2	86.66	83.93	90.12	86.91	91.46	89.53	90.49	87.05	94.42	90.58

ACE-2 relation extraction

	HMM entity extractor			Markovian SCFG			Full TEG system (with 7 ROLE rules)		
	Recall	Prec	F	Recall	Prec	F	Recall	Prec	F
Role				67.55	69.86	68.69	83.44	77.3	80.25
Person	85.54	83.22	84.37	89.19	80.19	84.45	89.82	81.68	85.56
Organization	52.62	64.735	58.05	53.57	67.46	59.71	59.49	71.06	64.76
GPE	85.54	83.22	84.37	86.74	84.96	85.84	88.83	84.94	86.84

INC relation extraction

	Partial match results			Exact match results		
	Recall	Prec	F	Recall	Prec	F
PersonAffiliation	89.61	94.52	**92.00**	75.33	79.46	**77.33**
OrgLocation	85.32	77.78	**80.00**	76.47	72.22	**74.29**
Acquisition	76.00	86.36	**80.85**	68.00	77.27	**72.34**

TEG - Potential

- Advantages
  - precise rules can be specified for arbitrary IE applications
  - external knowledge sources can be integrated via termlist
  - ngram-context for terminals via ngram (usable for disambiguation)
  - external systems can be integrated
    - „ngram ngOrgNoun featureset ExtPoS restriction Noun;“
- Possible innovations
  - Constraint based formalism as basis for grammar
  - Specialized parsing algorithms (e.g., supertagging)
  - Ontologies as basis for termlist
  - Extending grammars on basis of bootstrapping (human-controlled)
  - ...

Conclusion

- Hybrid IE as innovative plus for IE research and development.
- There exists already a number of promising and exciting approaches.
- High innovation potential to bring language technology, knowledge-based and statistical system under one umbrella.
- E.g., Multilingual Information Extraction
- E.g., Multi-Channel Information Extraction