# Domain Adaptive Relation Extraction for Big Text Data Analytics

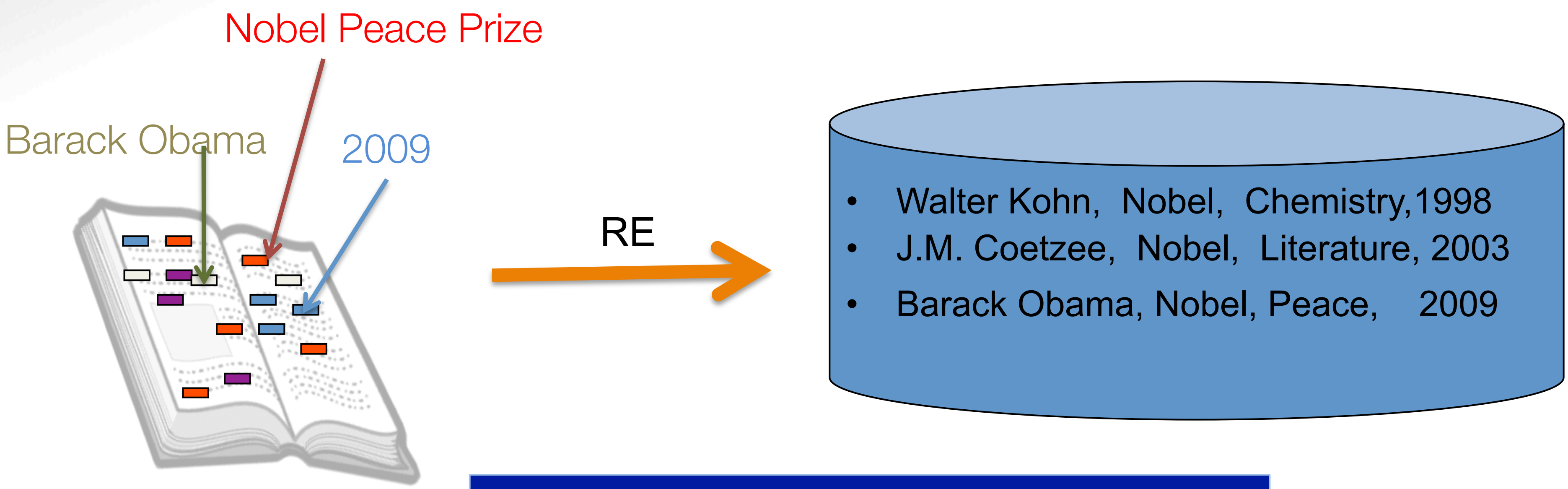
Feiyu Xu

# Outline

- Introduction to relation extraction and its applications
- Motivation of domain adaptation in big text data analytics
- Solutions
- Conclusion and future work

# What is Relation Extraction

- Given an unstructured text, a relation extraction (RE) tool should be able to automatically recognize and extract relations among the relevant entities or concepts that are salient to the user's needs




Linguistic Patterns*:*

- <*prize*> be awarded to <*person*>
- <*person*> win <*prize*> in <*year*>
- *……*

# Example in Opinion Mining

Mitten in der Euro-Krise geht ***Altkanzler Helmut Kohl*** mit *Angela Merkel* äußerst hart ins Gericht

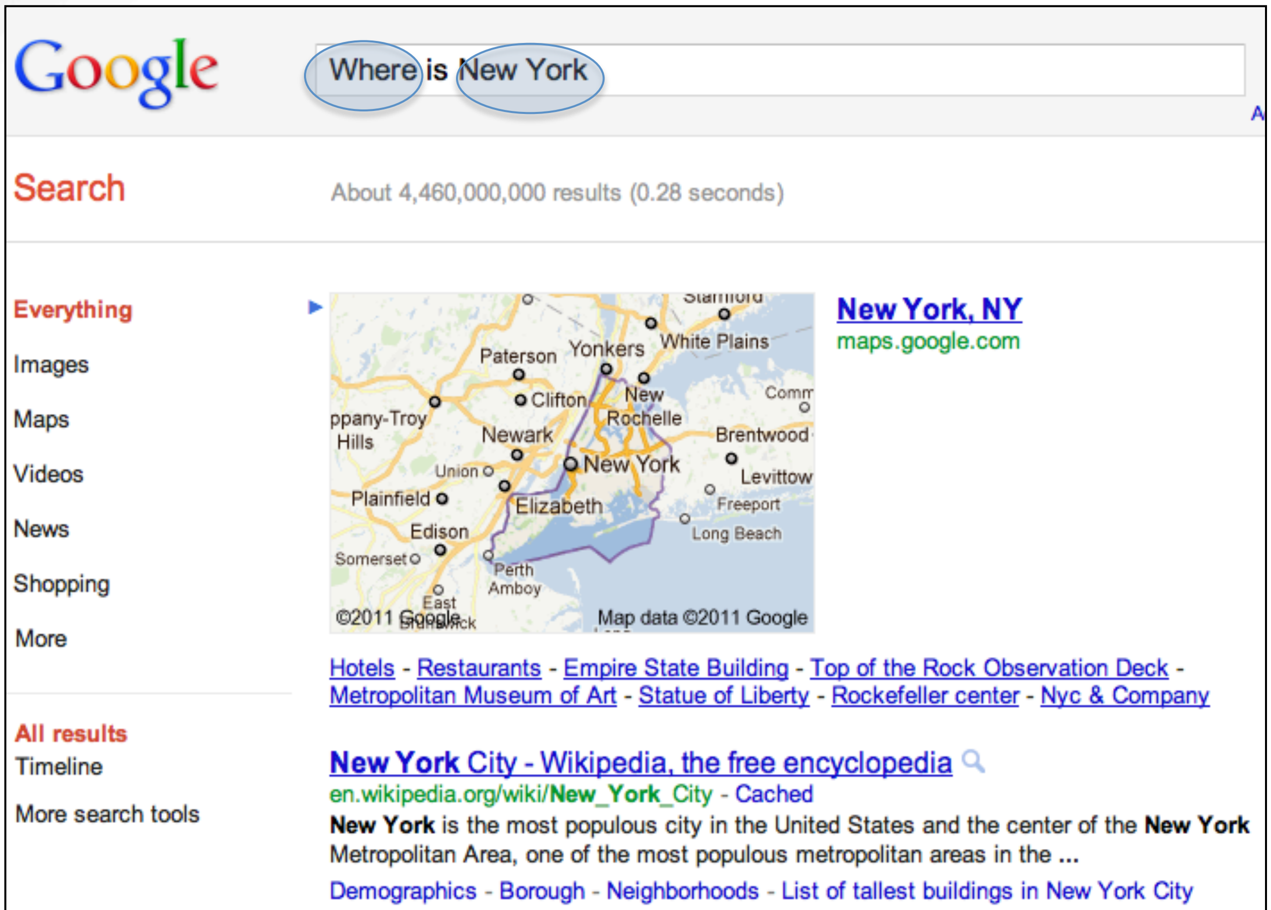
-- Welt online, 25.08.2011

**Opinion Holder** **Opinion Target** **Polarity**

# General application task 1:

☆ Information access for information finder

mapping unstructured textual queries of users to more structured formal query for search and answer engines



# General application task 2:

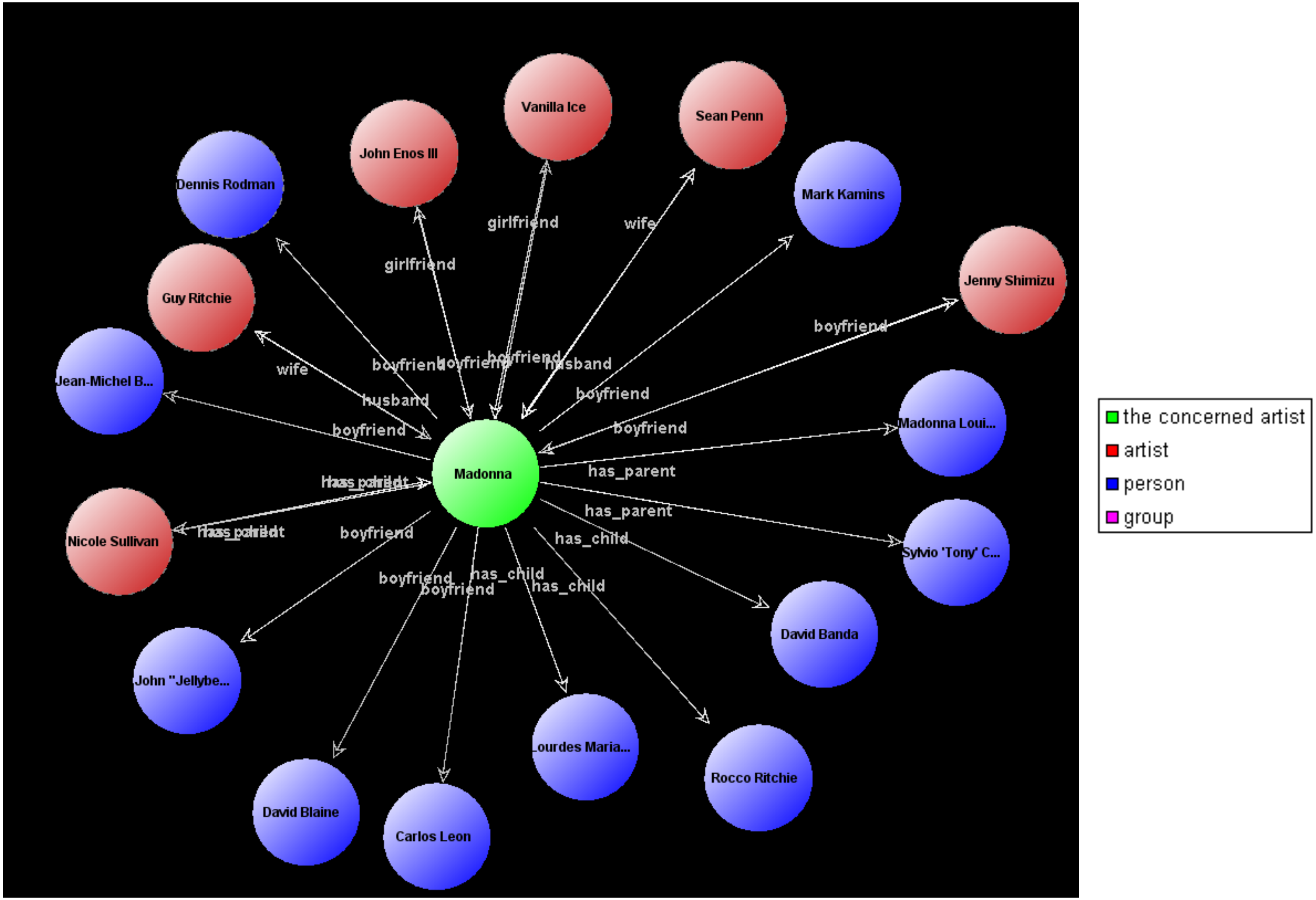
☆ Information acquisition for information provider

extract structured information from big amount free texts to construct knowledge bases

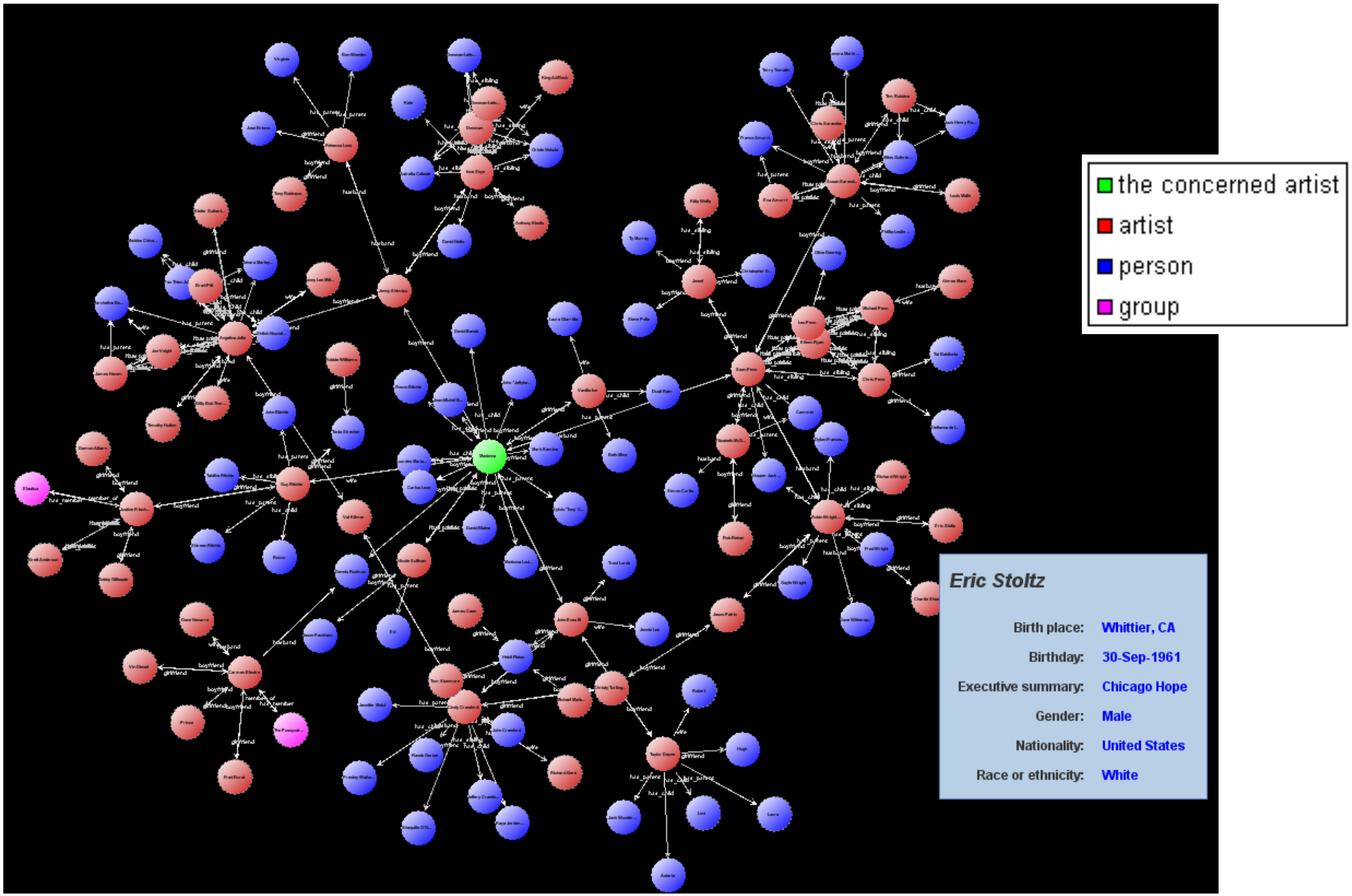
RE

# Acquisition of Social Network of Pop Stars from Web

Social Network of “Madonna” (Depth = 1)

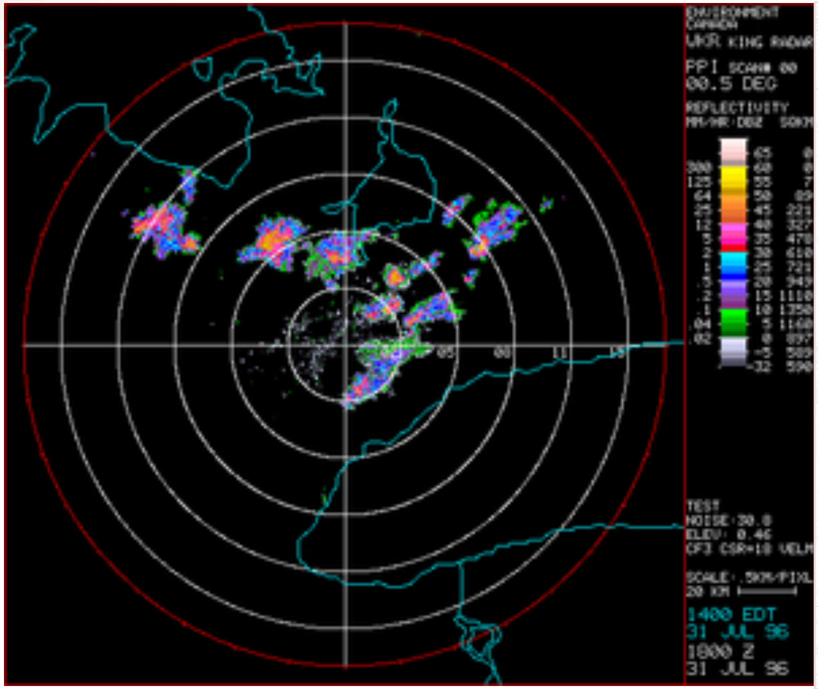


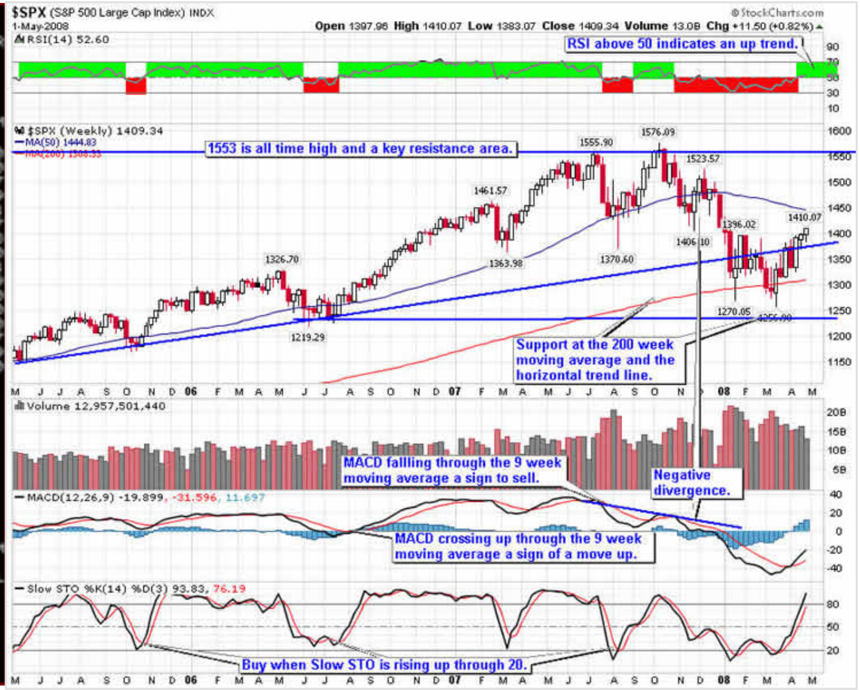
# Social Network of “Madonna” (Depth = 3)



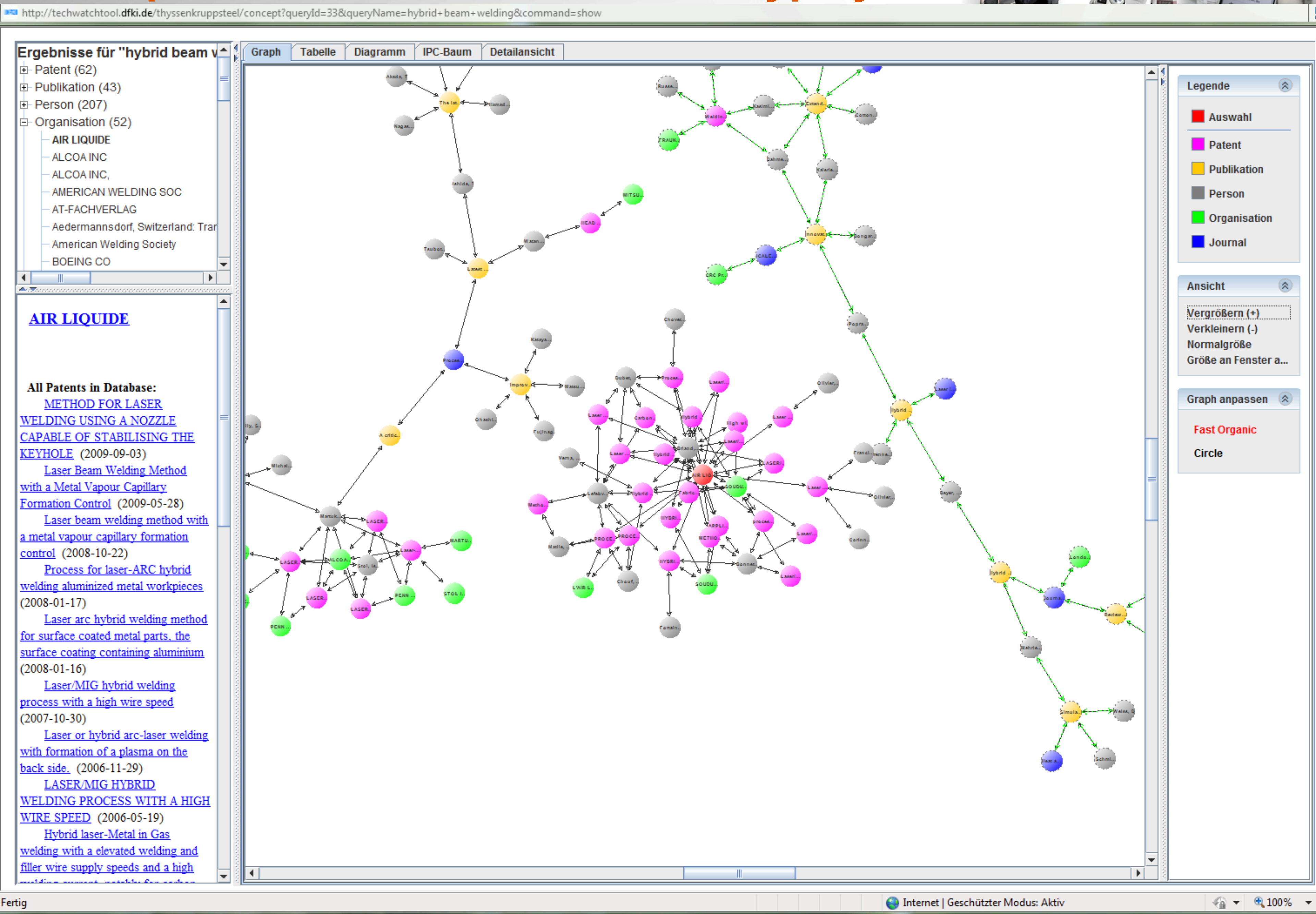
# General application task 3: Big Data Analytics

- Enabling the linking between structured and unstructured data
  - Large-scale information monitoring
  - Analytics: analyses of areas, markets, trends
  - Watch: Scanning for relevant new developments



# Example: Network of Innovation Keyplayers



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# Text Analytics for Big Textual Data

- Three main features of big data
  - *Volume*: *large-scale* in volume
  - *Variety*: with respect to heterogeneous domains and formats
  - *Velocity*: because of its rapid and steady growing.

- Requirements of text analytics technologies for big data
  - *efficient*
  - *robust*
  - *scalable*
  - *domain-adaptive*

# Domain Adaptation is Essential for Big Data!

- Among the three big data features, variety and velocity are even more challenging than the sheer size volume

# Reasons:

- New domains have been constantly emerging, rapidly growing in size.

- Domains can differ in
  - topics (e.g., medicine, chemistry or mechanics)
  - genres (e.g., news, novels, blogs, scientific publications or patents)
  - targets (e.g., different relations such as marriage, person-parent relation, disease-symptom relation)
  - data internal properties (e.g., size or redundancy or connectivity).
- Systems, methods or strategies developed or trained for so-called general purpose or one specific domain can often not be directly taken over by other domains, because
  - each domain needs its own domain knowledge and
  - each application data has its own special properties.

# Relevant Strategies for Domain Adaptation

- Minimally dependent on the labeled training data
  - Minimally or weakly supervised machine learning methods
- Strategies for
  - confidence estimation of automatically learned information and knowledge
  - filtering of irrelevant and wrong information
- Domain adaptation of generic systems for specific applications

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# Our solutions (1)

- **minimally supervised and distantly supervised automatic learning of domain-specific grammar-based pattern rules for n-ary RE: DARE and Web-DARE Systems**
  - Feiyu Xu, Hans Uszkoreit, Hong Li, “A Seed-driven Bottom-up Machine Learning Framework for Extracting Relations of Various Complexity (2007)”. In ACL 2007.
  - Hans Uszkoreit, Feiyu Xu, Hong Li. “Analysis and Improvement of Minimally Supervised Machine Learning for Relation Extraction”. In NLDB 2009.
  - Sebastian Krause, Hong Li, Hans Uszkoreit, Feiyu Xu, “Large-Scale Learning of Relation-Extraction Rules with Distant Supervision from the Web”. In Proceedings of the 11th International Semantic Web Conference (ISWC 2012).

# Our solutions (2)

- **Various filtering and confidence estimation methods for high-performance and large-scale relation extraction**
  - Sebastian Krause, Hong Li, Hans Uszkoreit, Feiyu Xu, “Large-Scale Learning of Relation-Extraction Rules with Distant Supervision from the Web”. In Proceedings of the 11th International Semantic Web Conference (ISWC 2012)
  - Andrea Moro, Hong Li, Sebastian Krause, Feiyu Xu, Roberto Navigli, Hans Uszkoreit, “Semantic rule filtering for web-scale relation extraction”. In Proceeding of International Semantic Web Conference (ISWC 2013).
  - Feiyu Xu, Hans Uszkoreit, Sebastian Krause, Hong Li. Boosting Relation Extraction with Limited Closed-World Knowledge. COLING 2009, Poster.

# Our solutions (3)

- **Automatic adaptation and improvement of generic parsing results for specific domains**
  - Peter Adolphs, Feiyu Xu, Hans Uszkoreit, Hong Li, “Dependency Graphs as a Generic Interface between Parsers and Relation Extraction Rule Learning”. In Proceedings of KI 2011, pp. 50-62, 2011.
  - Feiyu Xu, Hong Li, Yi Zhang, Hans Uszkoreit, Sebastian Krause, “Parse reranking for domain-adaptive relation extraction”. Journal of Logic and Computation, doi: 10.1093/logcom/exs055, Oxford University Press, 2012.

# Our solutions (4)

- **Automatic generation of domain-specific linguistic knowledge resources**
  - Hans Uszkoreit and Feiyu Xu, “From Strings to Things, SAR-Graphs: A New Type of Resource for Connecting Knowledge and Language”. In Proceedings of 1st International Workshop on NLP and DBpedia volume 1064, Sydney, NSW, Australia, CEUR Workshop Proceedings, 10/2013
  - **Open source: sargraph.dfki.de**

# Web-DARE
# Distant-supervised Web-scale RE

# Web-DARE: Distant Supervision based RE

- Large number of RE rules are automatically learned by using Freebase as seed knowledge and Web as training corpus
- Goal:
  - covering most linguistic variants for expressing a relation
  - thus solving the notorious long-tail problem of real-world NL applications

# Data Set

- rules learned for 39 relations
  - n-ary relations  n>=2
- three domains: business, awards and people
- 2.8 million relation instances retrieved from Freebase as seed
- 20 million web documents as training corpus

# Example in Nobel Prize Award Domain

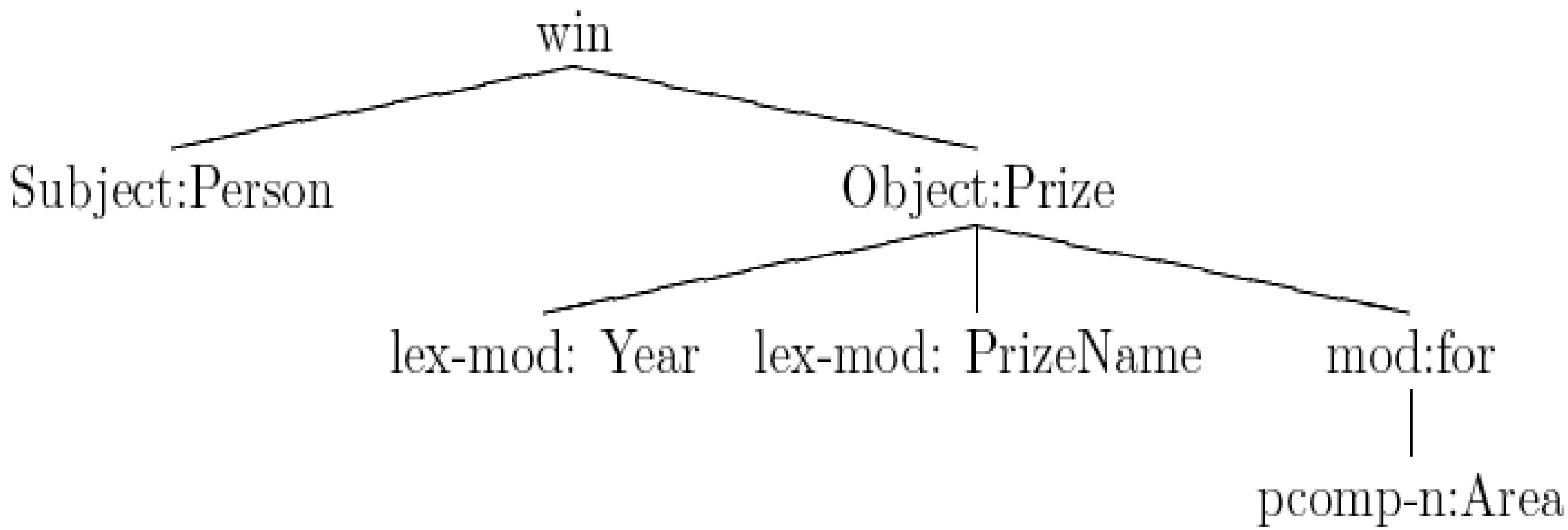
- Seed example

*<Mohamed ElBaradei/Person, Nobel/Prize, Peace/Area, 2005/Year>*

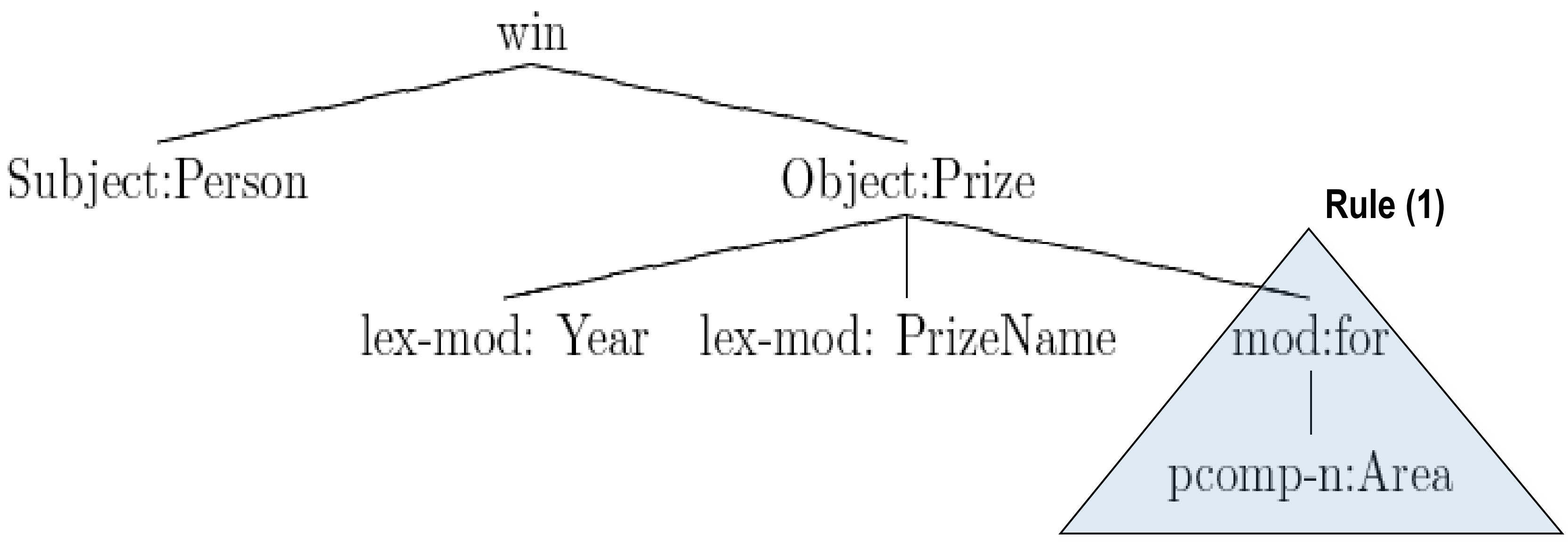
- Sentence matched with the seed

Mohamed ElBaradei won the 2005 Nobel Prize for Peace on Friday ...

# Dependency Parse Result



# Bottom Up Rule Learning



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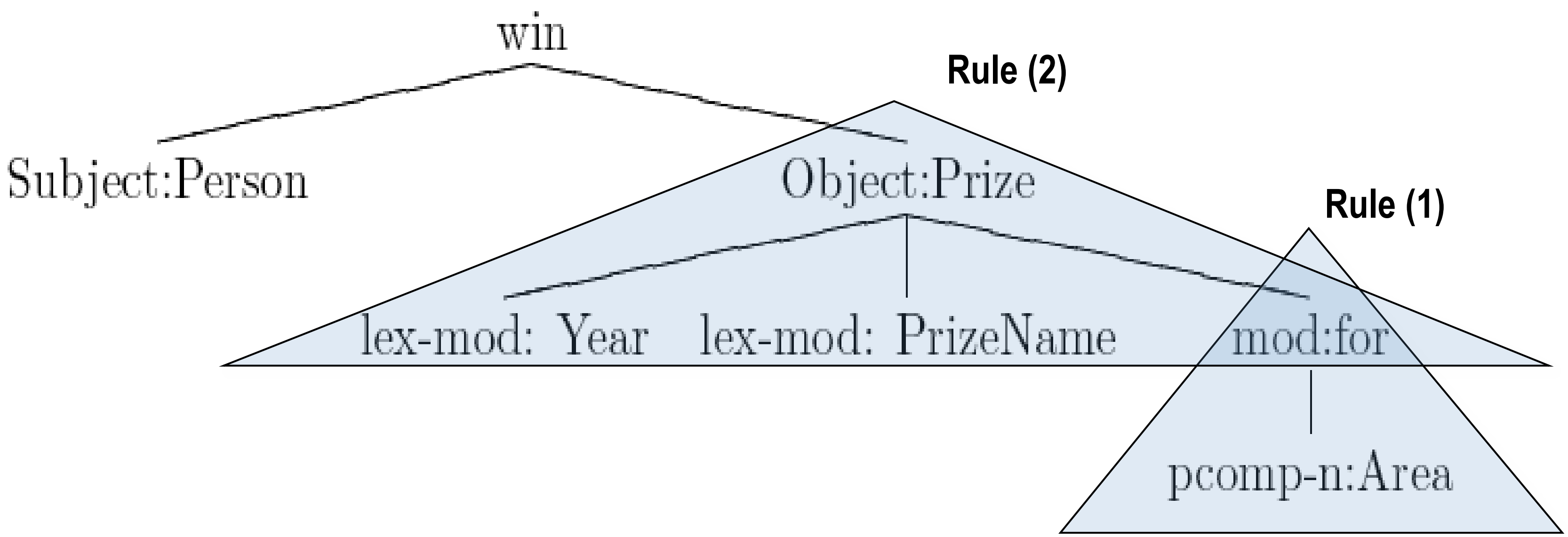

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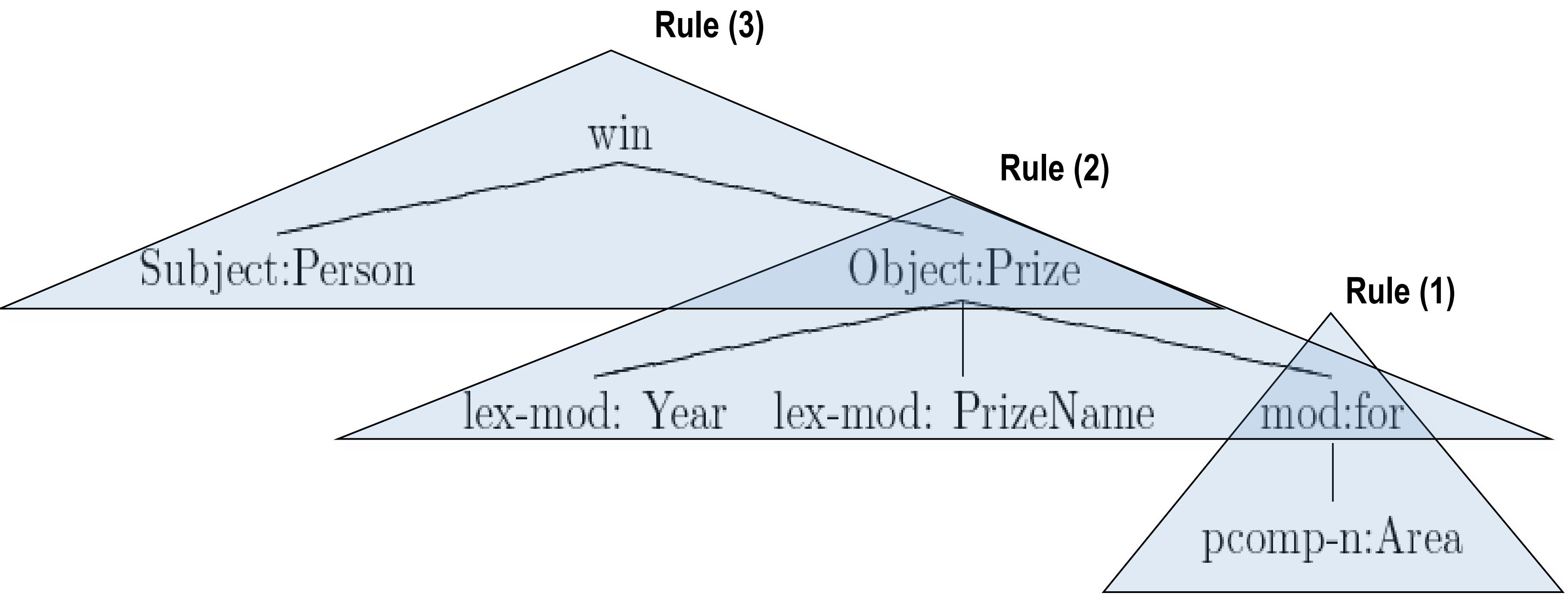
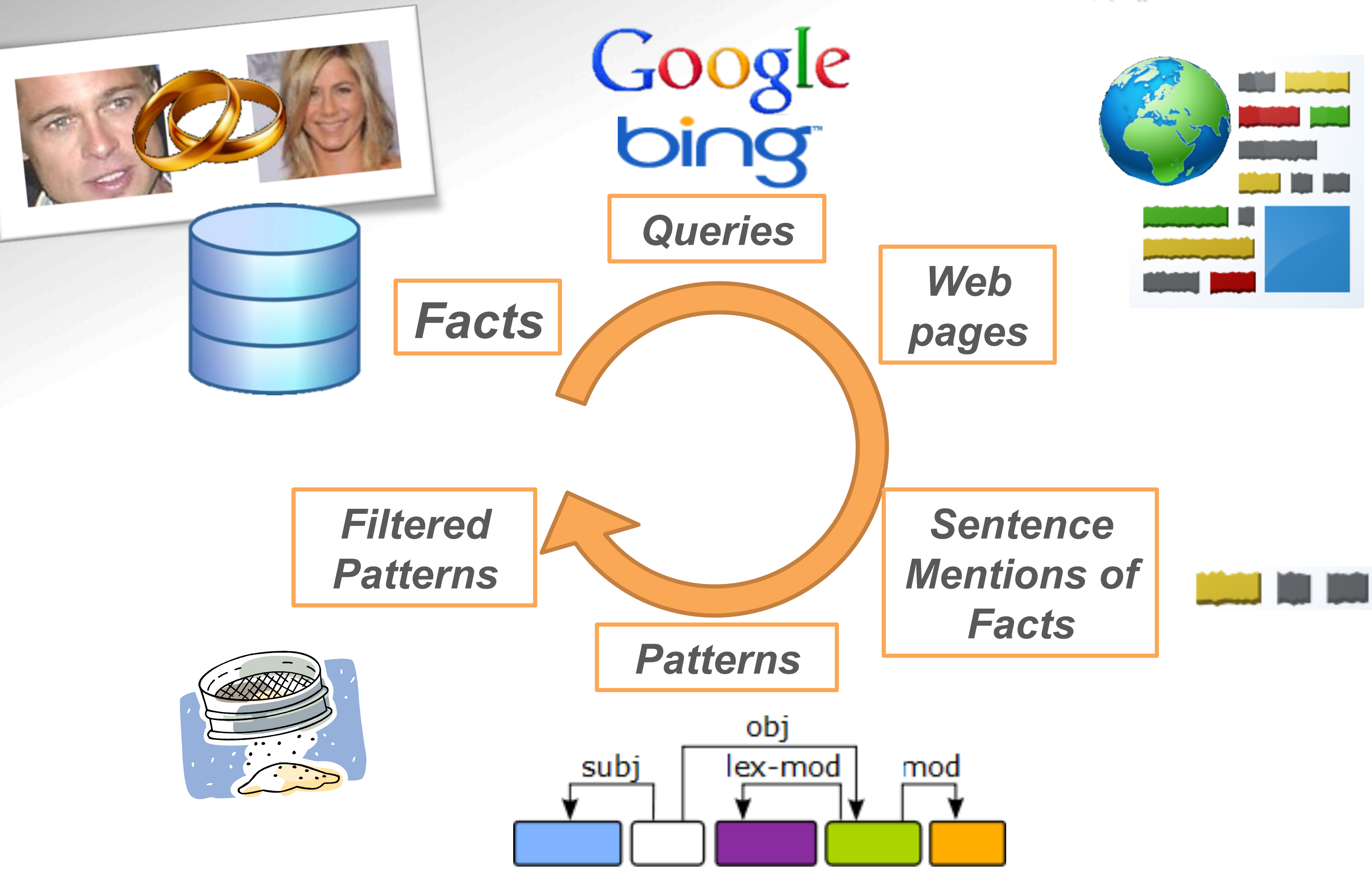


# Web-DARE Architecture



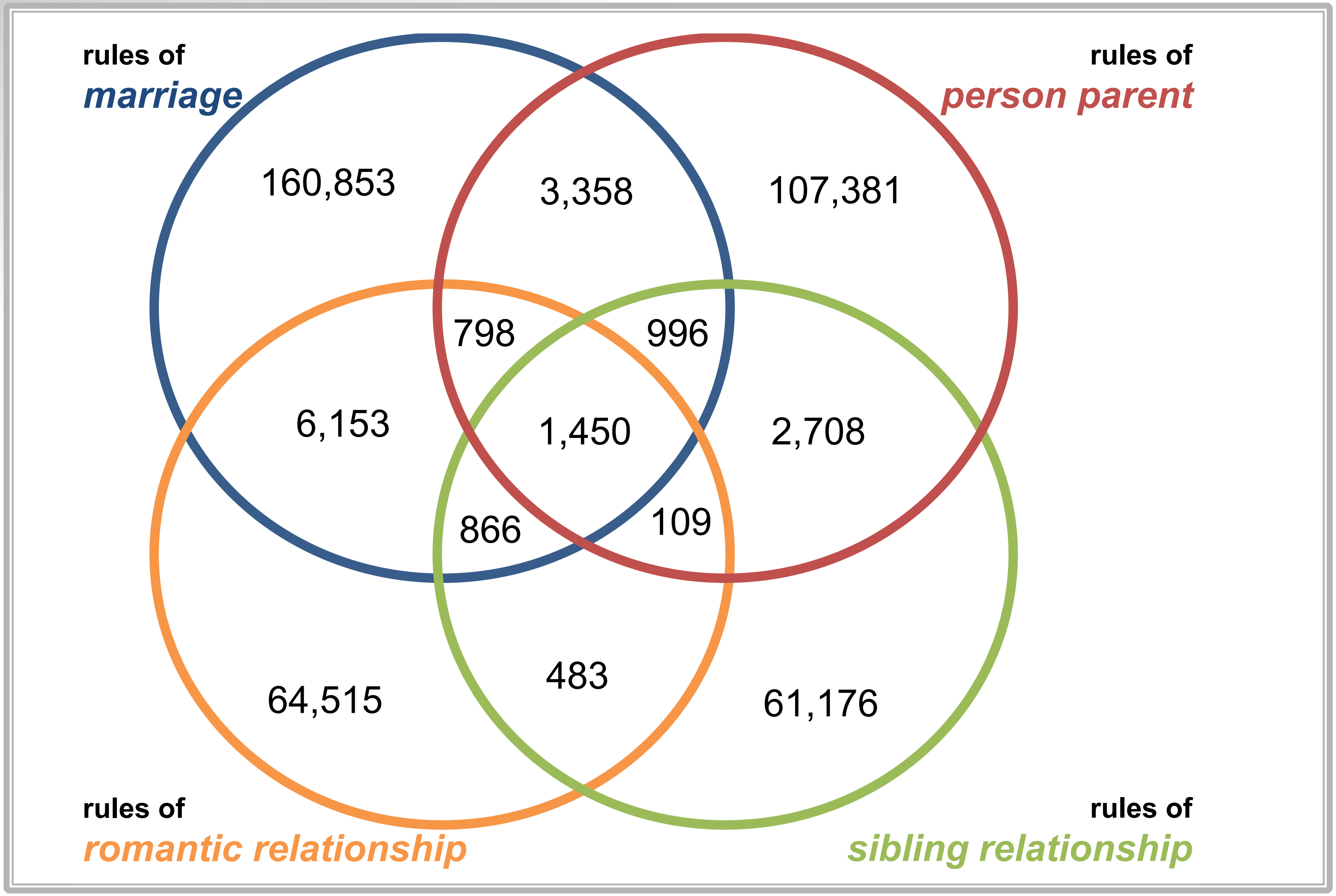
# Some Statistics of Web-DARE Rules

| Relation | # Sentences used | # Sentences w/ a learned rule | # Rules | # Rules w/o duplicates |
|---|---|---|---|---|
| *award nomination* | 13,966 | 13,149 | 23,987 | 7,800 |
| *award honor* | 50,550 | 49,001 | 106,550 | 40,578 |
| *hall of fame induction* | 31,244 | 28,278 | 44,920 | 17,450 |
| *organization relationship* | 46,331 | 42,824 | 60,379 | 28,903 |
| *acquisition* | 63,967 | 60,903 | 96,747 | 50,544 |
| *organization merger* | 2,996 | 1,521 | 3,243 | 1,758 |
| *company name change* | 9,433 | 9,132 | 15,619 | 6,910 |
| *spin off* | 5,247 | 5,094 | 8,319 | 4,798 |
| *marriage* | 342,895 | 335,313 | 557,478 | 176,949 |
| *sibling relationship* | 167,611 | 160,893 | 255,788 | 69,596 |
| *romantic relationship* | 155,335 | 152,878 | 229,393 | 74,895 |
| *person parent* | 192,610 | 186,834 | 390,878 | 119,238 |
| **average of 39 relations** | 66,545 | 66,509 | 109,435 | 41,620 |

# Problems of Large-Scale Approach

- Very low precision
  - a lot of noisy rules
  - many rules are learned from more than one relation

# Euler Diagram for Four People-Relations



# Various Filtering Strategies for High-Performance Web-Scale RE

# Frequency-Driven Rule Filters

- Merged Filter:

$$valid_{m}^{\mathcal{R}}(r) = valid_{freq}^{\mathcal{R}}(r) \wedge valid_{inter}^{\mathcal{R}}(r)$$

1) **absolute frequency filtering**: a threshold to exclude rules with low occurrency

# Rule Frequency Driven Filters

- Merged Filter:

$$valid^{\mathcal{R}}_{m}(r) = valid^{\mathcal{R}}_{freq}(r) \wedge valid^{\mathcal{R}}_{inter}(r)$$

1) **absolute frequency filtering**: a threshold to exclude rules with low occurrency
2) **inter-relation filter (Overlap Filter – FO Filter):**
   - based on mutual exclusiveness of relations with similar entity-type signatures.
   - a rule is only valid for a relation, if its relative frequency is higher than any other relations with similar entity type signatures.

$$valid^{\mathcal{R}}_{inter}(r) = \begin{cases} true & \text{if } \forall \mathcal{R}' \in \mathbb{R} \backslash \{\mathcal{R}\} : rf_{r,\mathcal{R}} > rf_{r,\mathcal{R}'} \\ false & \text{otherwise} \end{cases}$$

# Weakness of Filtering with Frequency

- Undetected low-quality patterns:
  - high frequency in target relation, low frequency in coupled relations

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nsubj dobj

PERSON Verb: “meet” PERSON

✗ ?

✔ ?

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- Undetected low-quality patterns:
  - high frequency in target relation, low frequency in coupled relations

nsubj dobj

PERSON Verb: "meet" PERSON

✗ ?

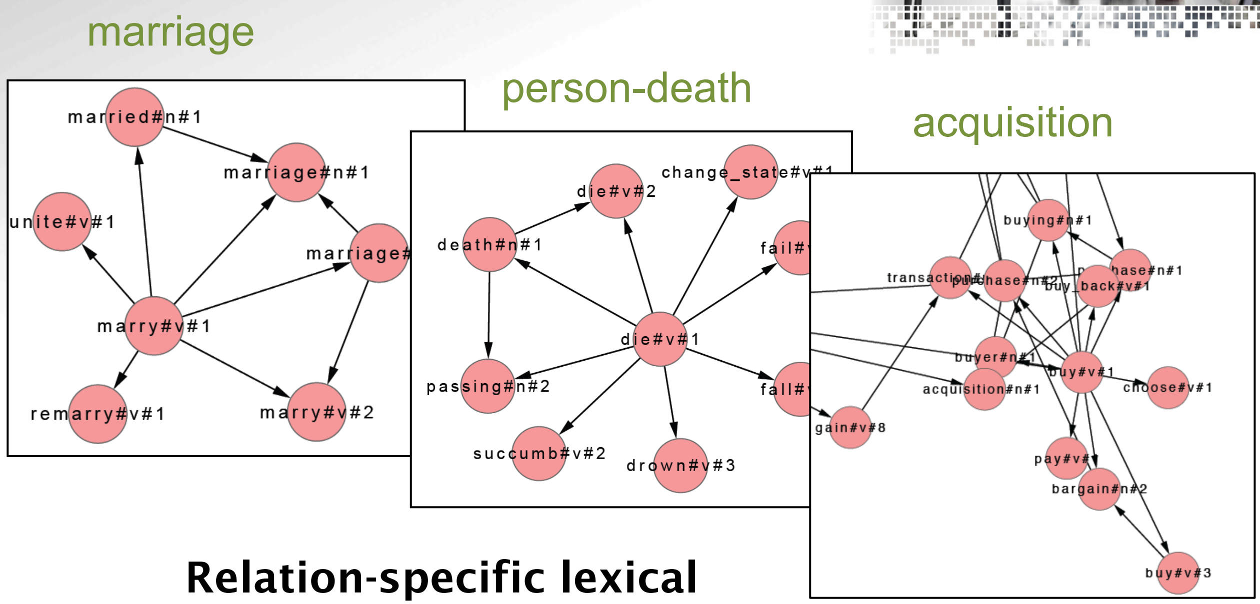
- Erroneously-deleted good patterns:
  - infrequent patterns

poss appos

PERSON Noun: "widower" PERSON

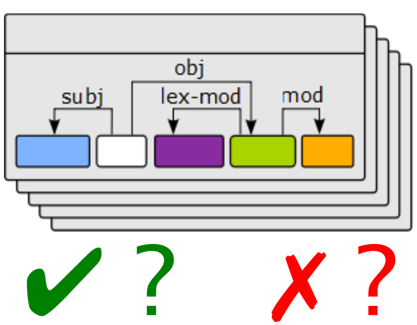
✔ ?

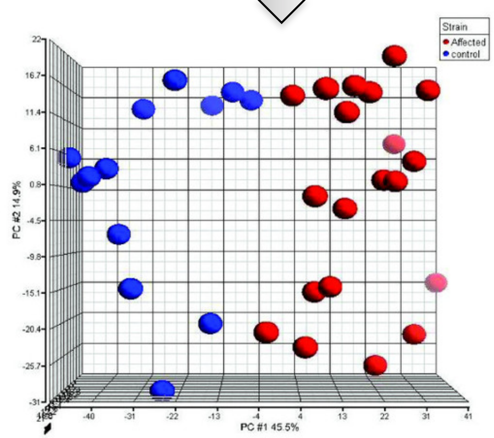
# Lexical Semantics can help!

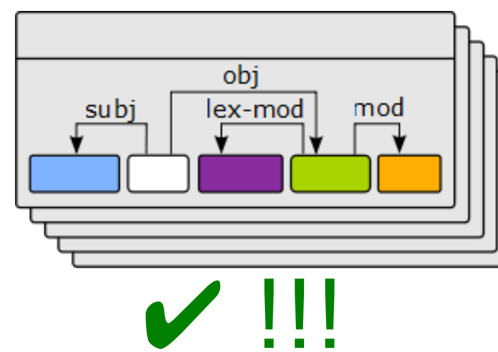



World Wide Web

Relation-specific lexical semantic graphs



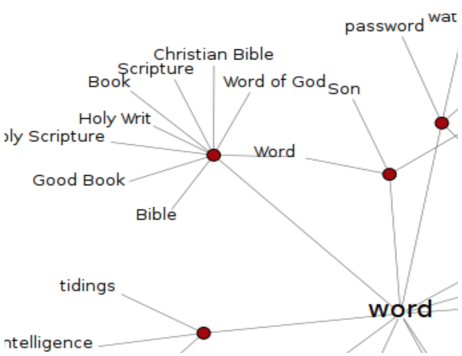

Candidate RE Patterns

Unsupervised Classification

High-quality RE Patterns

# Automatic learning of relation-specific lexical semantic network

Generic Lexical Semantic Network (BabelNet)




automatically learned unfiltered RE rules and their mentions

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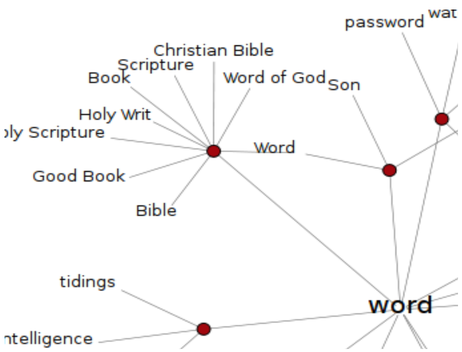
Generic Lexical Semantic Network (BabelNet)

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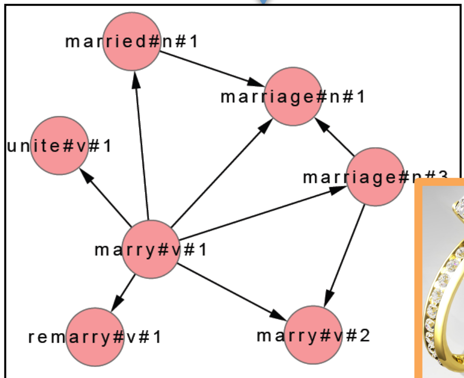
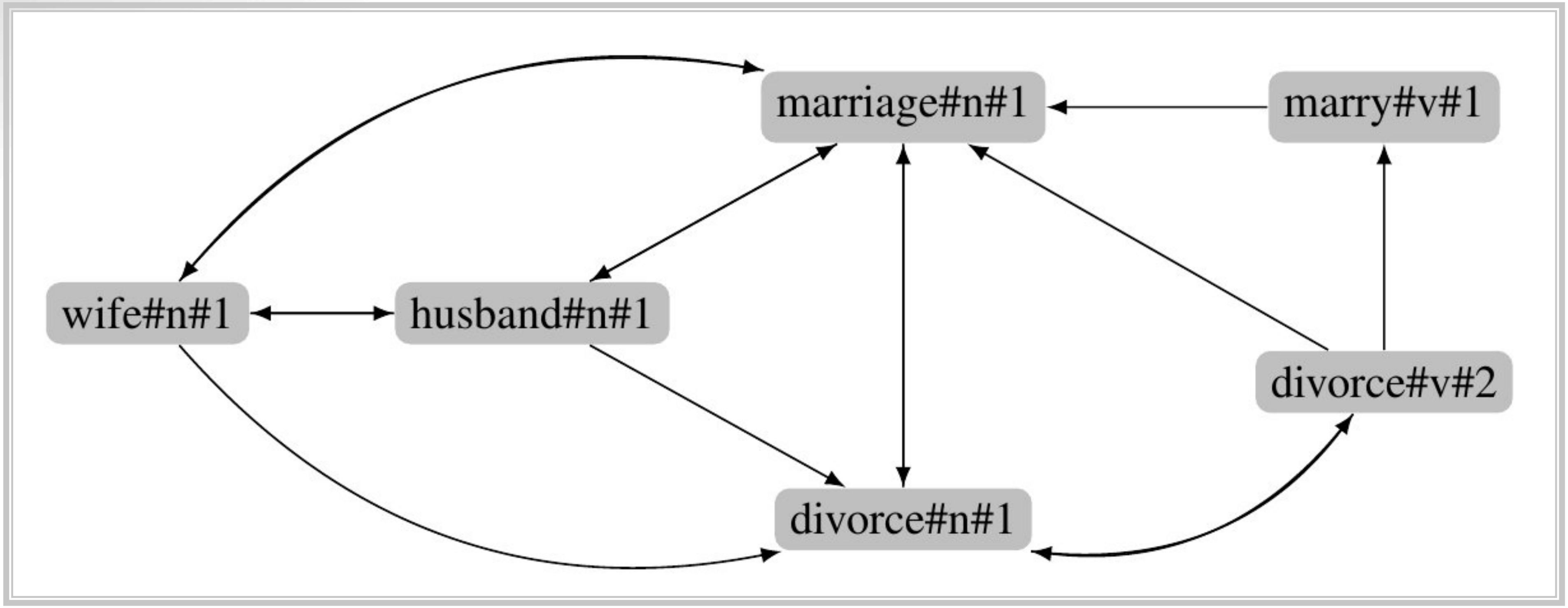
Word Sense Disambiguation

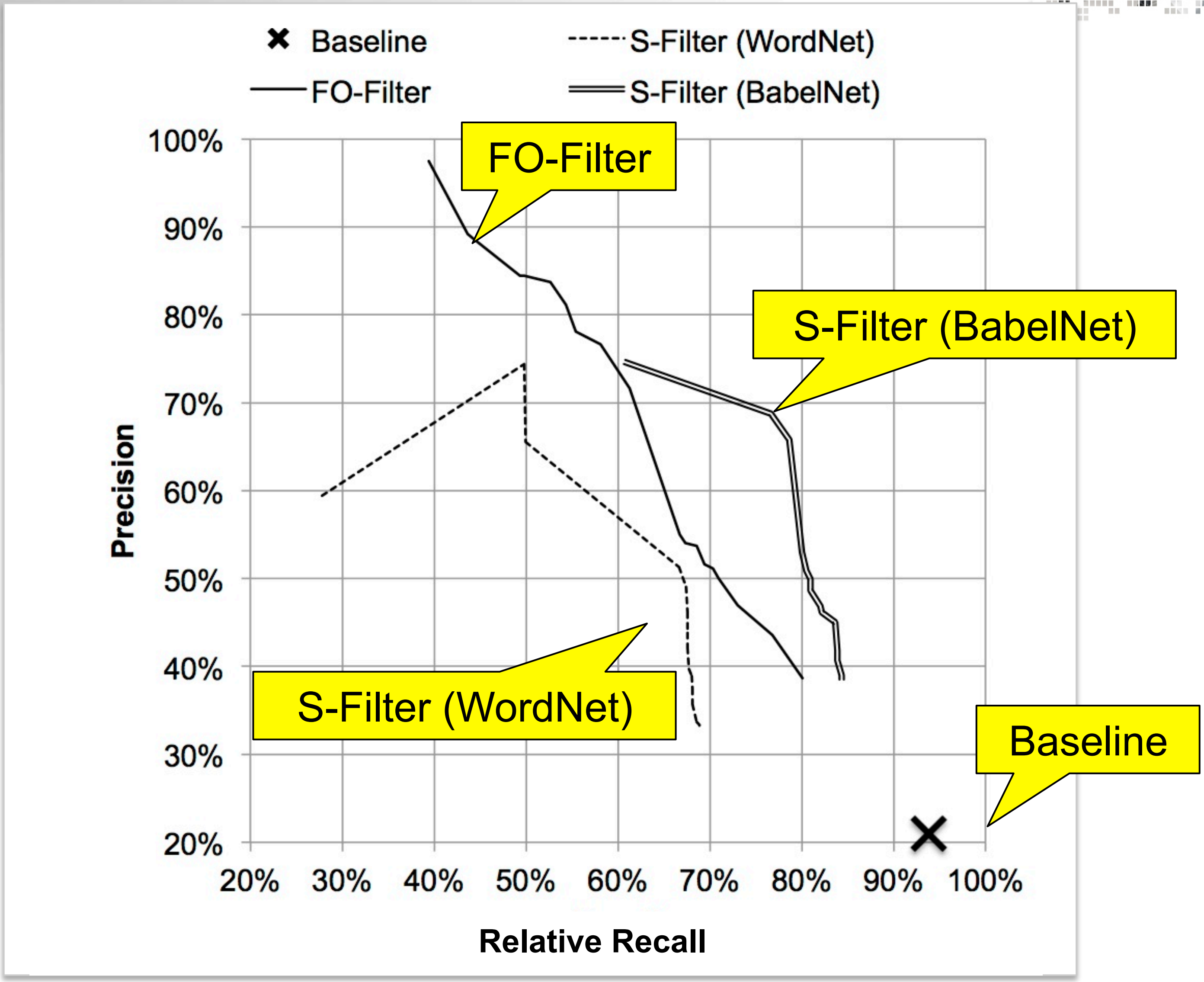



# The Relation-Specific Semantic Graph

An excerpt of the semantic graph for the relation *marriage*



# Extrinsic Eval. – Web-DARE



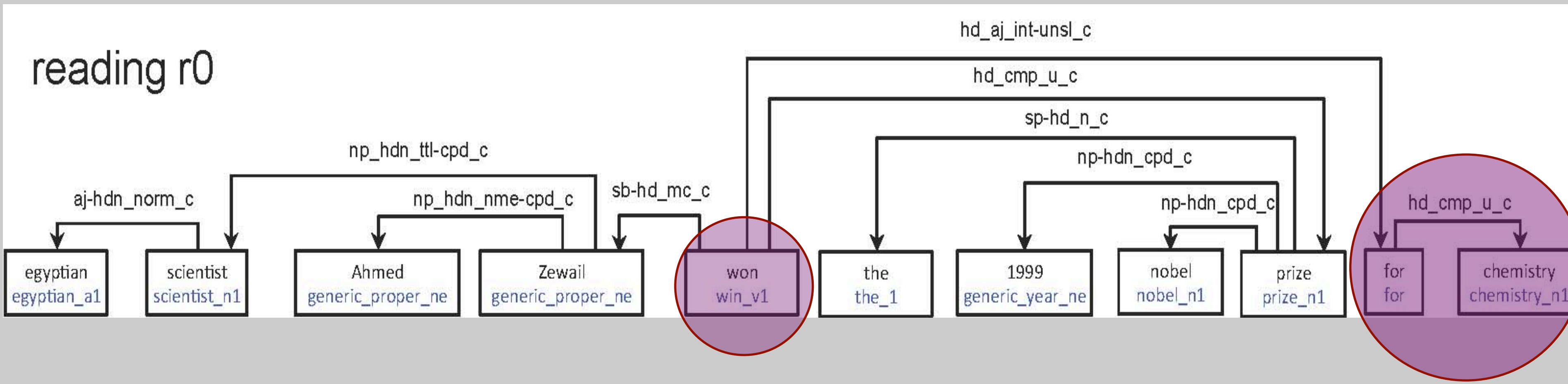

# Parse-Reranking for Domain-adaptive RE

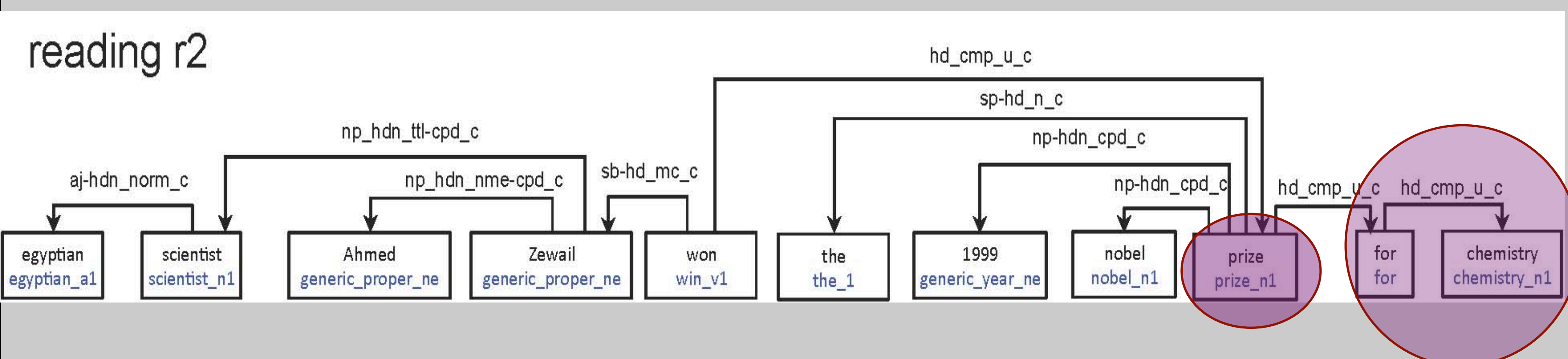
# Error Types of Extracted Wrong Instances

| Content | Modality | Named Entity Recognition (NER) | Parsing | NER & Parsing | DARE Rules |
|---|---|---|---|---|---|
| 11.8% | 17.6% | 5.9% | 38.2% | 11.8% | 14.7% |

# HPSG Parses: PP Attachment

***Egyptian scientist Ahmed Zewail won the 1999 Nobel Prize for chemistry***



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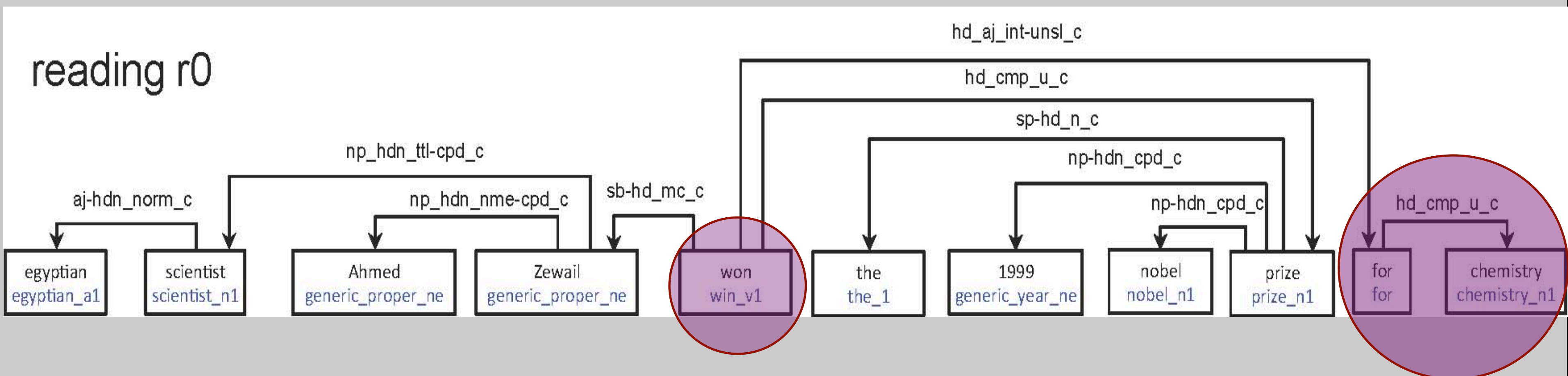
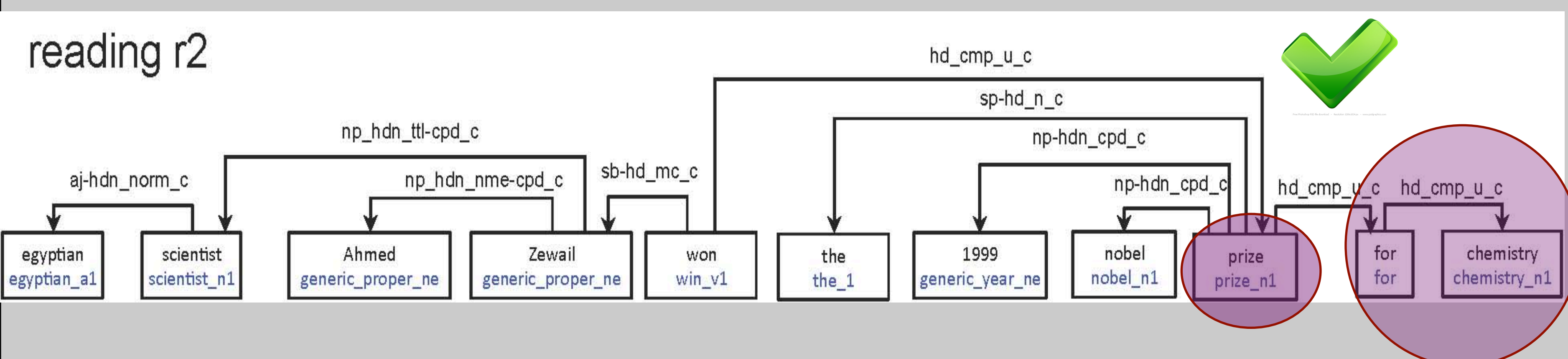
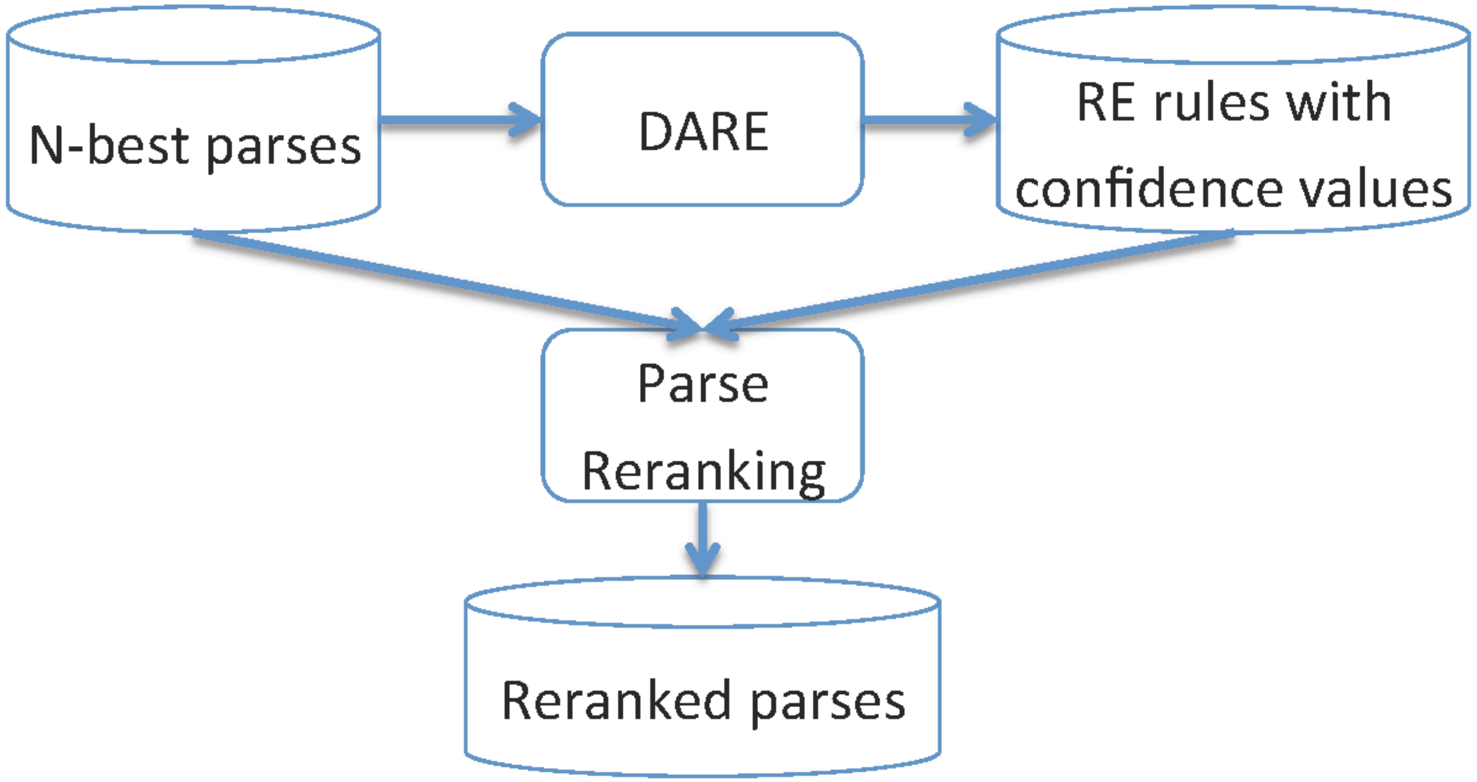


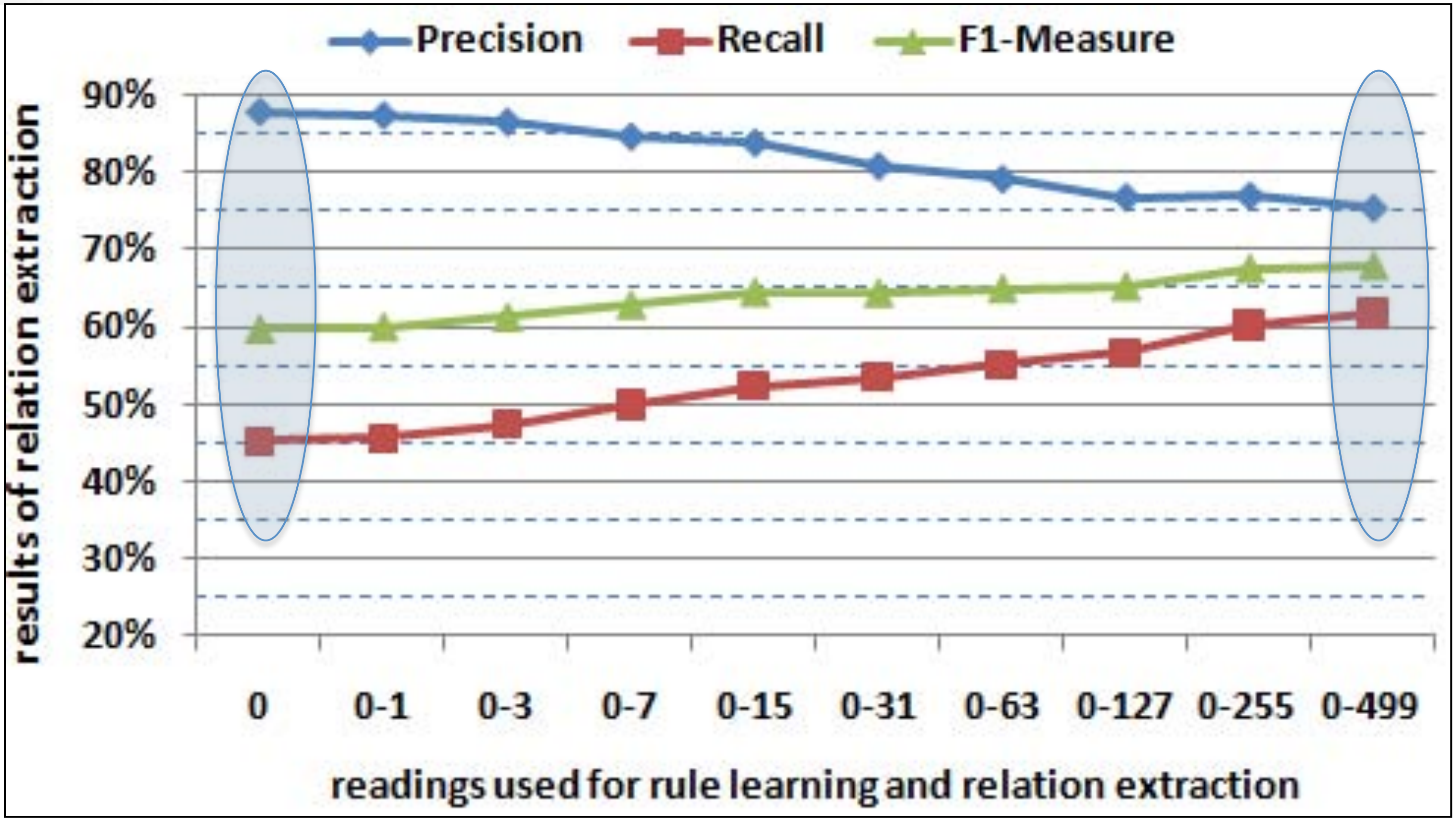



# Reranking Architecture



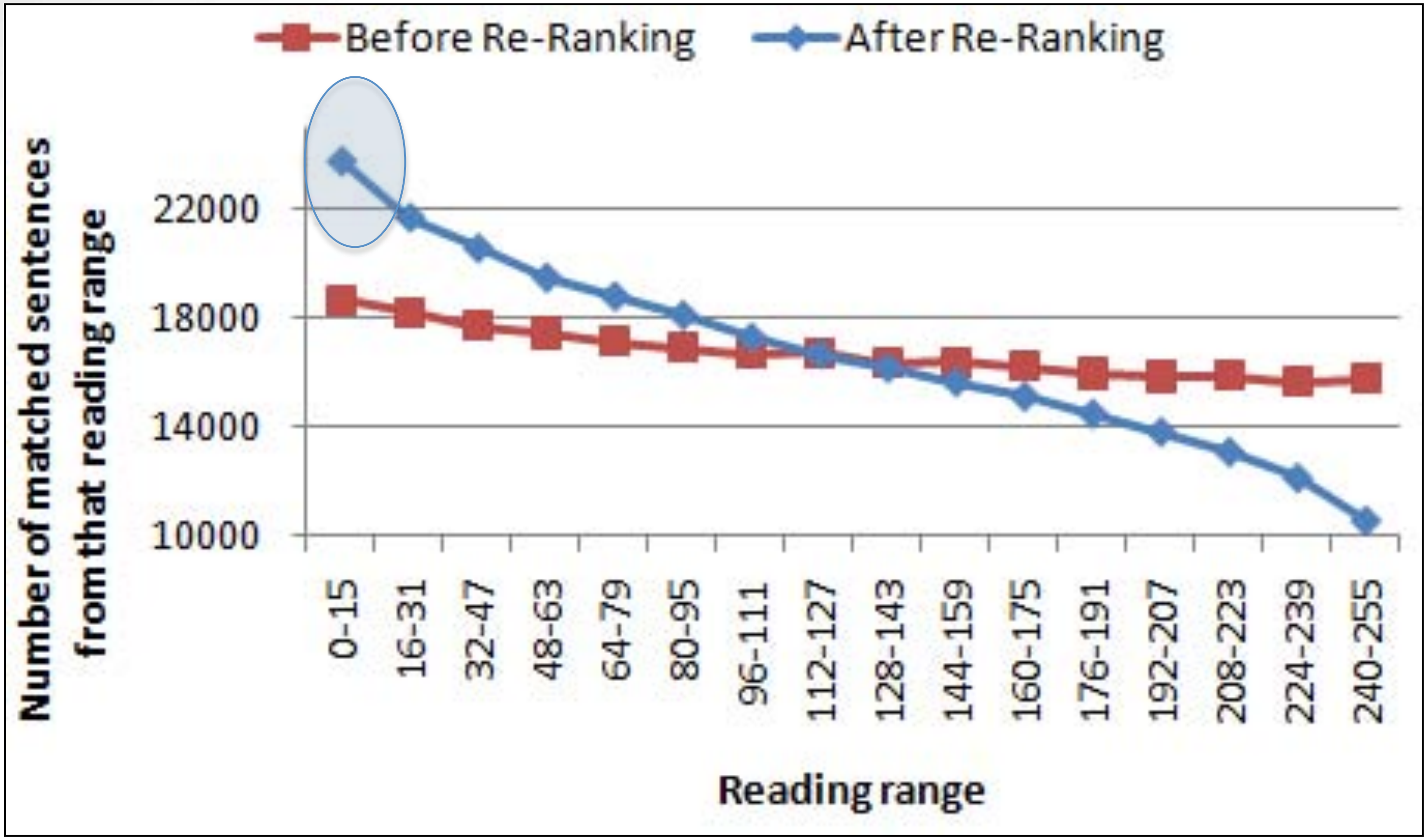
# Baseline: before Re-ranking

- **Best reading**: high precision, low recall, low F-measure
- **500 readings**: lower precision, higher recall, higher F-measure



# After Re-Ranking:

- Re-ranked top readings match more sentence mentions containing RE instances
- Improvements of Recall and F-Measure



# Conclusion

- The performance of large-scale RE for each application is dependent on the performance of domain-adaptation methods

- Three original contributions (among others):

  - Extension of relation extraction to n-ary relations

  - Semantic filtering with large lexical knowledge bases

  - Parser improvement for the specific RE task by reranking

- For our work we received a Google Focused Research Award

Google
Focused Research Awards

# Planned Future Work

- Immediate next step of big text data analytics is to integrate the existing NLP and IE components into big data analytics platforms
- Entity linking and RE will play an essential role for semantic interoperability between structured and unstructured data
- Extension and Application of our IE technologies to the new Smart Data projects
  - Smart Data Web: Industry 4.0
  - Smart Data for Mobility: Mobility