# Almost Total Recall: Semantic Category Disambiguation Using Large Lexical Resources and Approximate String Matching

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## **Semantic Category Disambiguation** These findings suggest that SalK/SalR requisite for the full virulence of ethnic Chinese... Figure: Demarked textual spans requisite for the full virulence of ethnic Chinese... These findings suggest that SalK/SalR Figure: Demarked textual spans assigned semantic categories • Semantic Category Disambiguation: assign one or multiple semantic categories to a single continuous textual span Integral part of Named Entity Recognition (NER) **Research Target** How does semantic disambiguation perform in an NLP pipeline? Can it minimise the number of categories exposed to an annotator? **Previous Research** Cohen et al. (2011) Define categories by ontologies Associate a textual span with one or multiple categories Rule-based, non-probabalistic Stenetorp et al. (2011) Standard NER features

## Approach

20,335,426 entries

Single category assumption

Machine learning, probabalistic

- Exploit the probabalistic aspects of the model
- Use the sum of the category probabalities to threshold the number of suggestions

Novel large-scale fast approximate string matching with 170 databases and

Forces the model to perform a recall trade-off

### **Experimental Results**

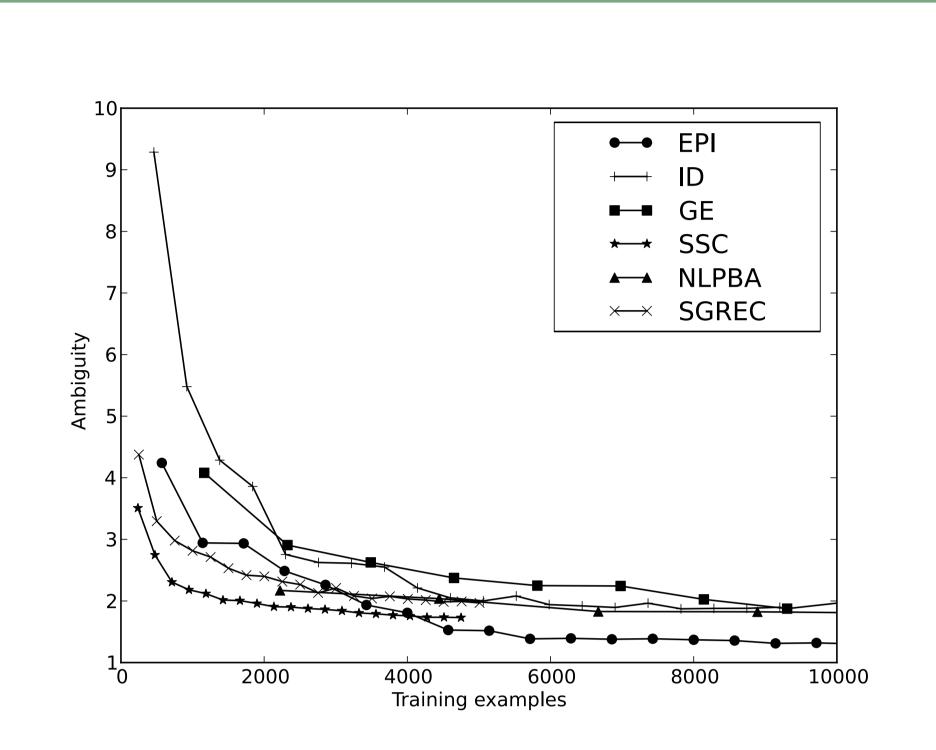


Figure: Ambiguity per dataset

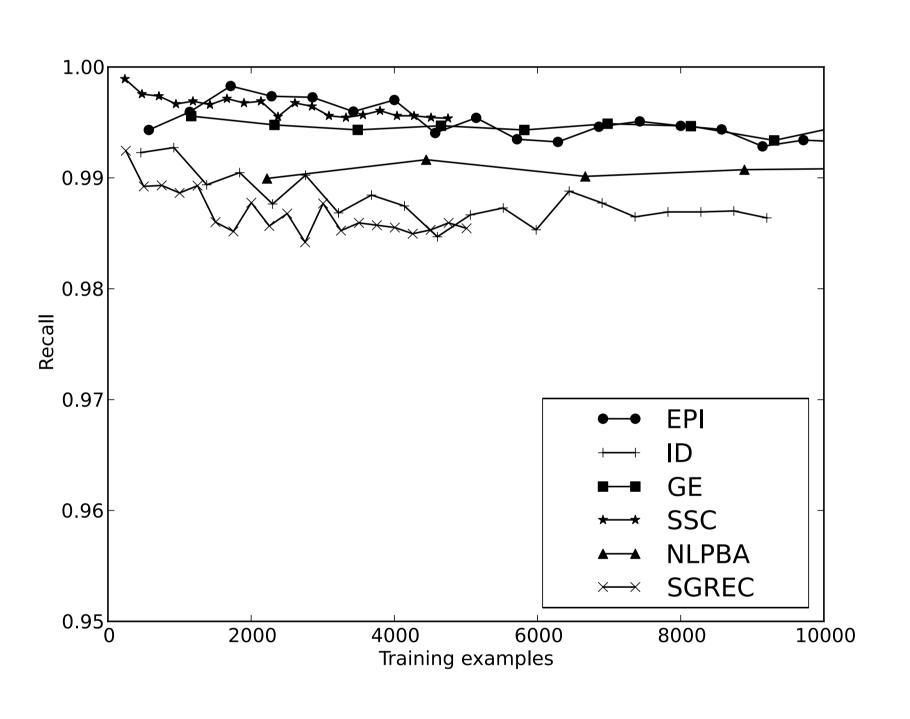


Figure: Recall per Dataset

Dat	a set	Mean Ambiguity	Ambiguity	Mean Recall	Recall
EP	I	1.8/89.4%	1.3/92.4%	99.5%	99.4%
ID		2.9/81.9%	1.9/88.1%	98.8%	98.6%
GE		2.1/80.9%	1.7/84.5%	99.4%	99.5%
SS	С	2.0/50.0%	1.7/57.5%	99.6%	99.5%
NL	PBA	1.8/64.0%	1.6/68.0%	99.1%	99.1%
SG	REC	2.4/60.0%	2.0/66.7%	98.7%	98.6%

Table: Performance by ambiguity level/reduction and recall for the mean over the learning curve and when all training and development data was used as training data

#### **Evaluation Datasets**

Name	Abbreviation	Semantic Categories
BioNLP/NLPBA 2004 Shared Task Corpus	NLPBA	5
Gene Regulation Event Corpus	SGREC	64 (5 collapsed)
Collaborative Annotation of a Large Biomedical Corpus	SSC	4
Epigenetics and Post-Translational Modifications	EPI	17
Infectious Diseases Corpus	ID	16
Genia Event Corpus	GENIA	11

Table: Corpora used for evaluation

#### **Evaluation Metrics**

- Ambiguity: average number of suggested categories
- Recall: as an ambiguity trade-off

#### Conclusions

- Can retain high recall while greatly reducing ambiguity
- Semantic category disambiguation is ready to support other tasks

#### **Future Work**

- Support other NLP tasks such as co-reference resolution and coordination
- Extend to Noun Phrase classification
- Does the results hold even when the amount of categories goes towards the hundreds?
- Integrate into existing annotation tool(s) as speed enhancement and quality checker

## Availability

Source code, lexical resources, additional results and future research is/will be available at:

http://github.com/ninjin/simsem/

Feel free to use, derive and/or complain.

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