

Bridging the Gap Between Scope-based and Event-based Negation/Speculation Annotations:

A Bridge Not Too Far

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Outset



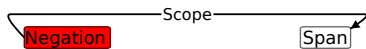
Outset



The Plan, Like So many Plans Before It

- Two separated research efforts
- A common goal
- Bringing them together in unification

CoNLL-2010 Shared Task Negation/Speculation Corpus

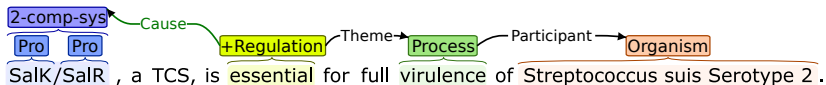


Surprisingly, however, **neither** of these proteins bound in vitro to EBS1 or EBS2 .

Background

- Used in the CoNLL-2010 Shared Task (Farkas et al. 2010)
- Linguistically motivated cue-and-scope annotations

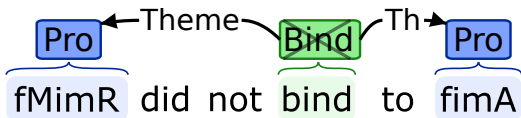
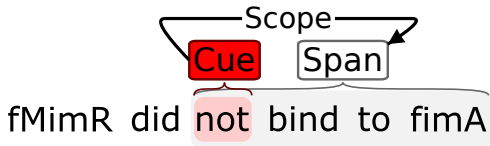
BioNLP Shared Tasks on Event Extraction (EE)



Background

- Introduced by Kim et al. (2009, 2011)
- Includes negation/speculation as a subtask
- Task-oriented binary flag annotations

Annotations Styles: Poles Apart?



Related Work

Kilicoglu and Bergler (2010)

- EE to extract cue-and-scope negation/speculation spans

Vincze et al. (2011)

- Manual analysis of negation/speculation annotation differences on the Genia EE and CoNLL-2010 corpus
- Found a multitude of problematic cases
- No proposed system to solve these issues

This Work

In a Single Question

- Can the efforts on the CoNLL-2010 Shared Task benefit those on event extraction?

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Approach

- Leverage existing systems for EE and negation/speculation
- Not duplicate previous efforts, join them
- Design inspired by manual analysis
- Propose a general solution

Data and Manual Analysis

Name	Neg. Events		Spec. Events		Neg. Spans	Spec. Spans
EPI	103	(5.6%)	70	(3.8%)	561	1,032
GE	759	(7.4%)	623	(6.0%)	1,308	1,968
ID	69	(3.3%)	26	(1.2%)	415	817

Table: Data sets from the BioNLP 2011 Shared Task (Kim et al. 2011)

Manual Analysis

- Vincze et al. (2011) analysis of GE
- Domain expert analysis of EPI and ID train sets

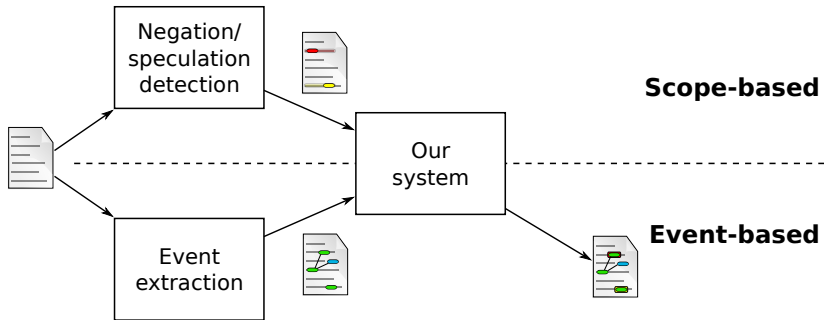
Manual Analysis Results

Analysis	Label	Ratio in EPI	Ratio in ID
Coverage	Covered	15.03	56.52
	Not-covered	78.03	41.30
	Error-in-gold	6.94	2.18

Manual Analysis Results

Analysis	Label	Ratio in EPI	Ratio in ID
Coverage	Covered	15.03	56.52
	Not-covered	78.03	41.30
	Error-in-gold	6.94	2.18
Non-covered	Morphological	27.75	11.96
	Hypothesis	25.43	16.30
	Ellipsis	2.89	0.00
	Argument-only	1.16	10.87

System Architecture



External Components

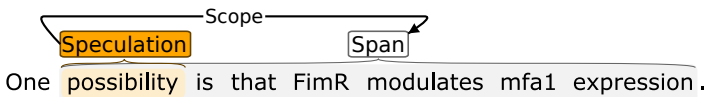
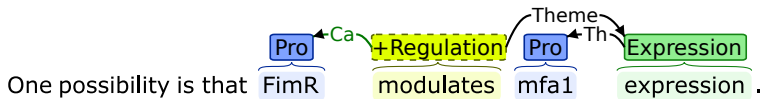
Negation/Speculation

- CLiPS-NESP (Morante et al. 2010)

Event Extraction

- UTurku (Björne et al. 2011)
- UConcordia (Kilicoglu and Bergler 2011)
- FAUST (Riedel et al. 2011)

Heuristic: Baseline



First Experiment

Set-up

- Negation/speculation from upstream system
- Gold event annotations
- Standard F-measure score

Heuristic: Negation Results

Negation	EPI	GE	ID
Heuristic-Baseline	30.40	53.38	36.97

Heuristic: Negation Results

Negation	EPI	GE	ID
Heuristic-Baseline	30.40	53.38	36.97
Heuristic-Root	30.00	61.18	40.74

Heuristic: Speculation Results

Speculation	EPI	GE	ID
Heuristic-Baseline	8.75	23.58	11.61

Heuristic: Speculation Results

Speculation	EPI	GE	ID
Heuristic-Baseline	8.75	23.58	11.61
Heuristic-Root	7.59	31.03	13.90

Machine Learning

Motivation

- Easier to incorporate complex features
- Re-trainable for different systems

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Machine Learning Procedures

- Tune penalty parameter using 10-fold cross-validation
- Merged training data
- Only final experiments on test set
- L2-regularised L2-loss SVM model

Machine Learning: Features

Group	Feature	Example Value(s)
Heuristic	Covered	ROOT/NON-ROOT
	Cue-Text	possibility
	Span-Tokens	One, possibility, ...

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	Trigger-Prefixes	no, non, non-, ...

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	Trigger-Prefixes	no, non, non-, ...
Contextual	Trigger-Preceding	is, that, ...
	Trigger-Proceeding	mfa1, expression, ...

Machine Learning: Negation Results

Negation	EPI	GE	ID
Heuristic-Baseline	30.40	53.38	36.97
Heuristic-Root	30.00	61.18	40.74
Trigger	28.18	31.82	33.82

Machine Learning: Negation Results

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Heuristic-Baseline	30.40	53.38	36.97
Heuristic-Root	30.00	61.18	40.74
Trigger	28.18	31.82	33.82
Heuristic+Trigger	62.90	63.69	60.67

Machine Learning: Negation Results

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Heuristic-Root	30.00	61.18	40.74
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Trigger+Context	52.00	66.15	56.52

Machine Learning: Negation Results

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Trigger+Context	52.00	66.15	56.52
Heuristic+Trigger+Context	64.96	70.84	63.74

Machine Learning: Speculation Results

Speculation	EPI	GE	ID
Heuristic-Baseline	8.75	23.58	11.61
Heuristic-Root	7.59	31.03	13.90
Trigger	0.93	15.24	17.19

Machine Learning: Speculation Results

Speculation	EPI	GE	ID
Heuristic-Baseline	8.75	23.58	11.61
Heuristic-Root	7.59	31.03	13.90
Trigger	0.93	15.24	17.19
Heuristic+Trigger	5.88	29.00	28.57

Machine Learning: Speculation Results

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Machine Learning: Speculation Results

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Trigger	0.93	15.24	17.19
Heuristic+Trigger	5.88	29.00	28.57
Trigger+Context	52.43	35.37	33.96
Heuristic+Trigger+Context	49.50	40.00	37.21

Second Experiment: Enrichment

Set-up

- Negation/speculation from upstream system
- Event annotations from three upstream systems
- Global F-measure score
- EPI and ID data sets
- Heuristic+Trigger+Context model

Enrichment: Results

F-score	EPI	ID
UConcordia	27.88	44.21
UConcordia*	28.05	45.19

Enrichment: Results

F-score	EPI	ID
UConcordia	27.88	44.21
UConcordia*	28.05	45.19
UTurku	53.33	42.57
UTurku*	54.29	42.19

Enrichment: Results

F-score	EPI	ID
UConcordia	27.88	44.21
UConcordia*	28.05	45.19
UTurku	53.33	42.57
UTurku*	54.29	42.19
FAUST	35.03	55.59
FAUST*	37.21	55.88

Conclusions and Future Work

Conclusions

- Yes, we can bridge the gap!
- Introduced a practical way to do so
- Performed better than several existing EE systems
- Achieved state-of-the-art performance

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Future Work

- Ways to eliviate hypothesis
- Other negation/speculation systems
- Use upstream confidence and/or integrate into EE system

Thank You for Your Attention

ご清聴ありがとうございました

Tack för er uppmärksamhet

Code: <http://ninjin.github.com/eepura/>
Slides: <http://pontus.stenatorp.se/>



Additional Negation Enrichment Results

Negation	EPI	GE	ID
UConcordia	26.51	25.88	22.92
UConcordia*	31.17	27.42	29.68
UTurku	18.60	31.15	32.91
UTurku*	45.53	27.33	32.10
FAUST*	39.18	28.25	35.00

Additional Speculation Enrichment Results

Speculation	EPI	GE	ID
UConcordia	6.82	27.25	3.23
UConcordia*	2.70	17.98	3.51
UTurku	37.65	23.06	15.00
UTurku*	46.60	15.60	4.76
FAUST*	41.76	14.93	12.50

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For the Interested and Lawyers

Visualisations

- Annotation visualisations generated using the brat annotation/visualisation tool: <http://brat.nlplab.org/>

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