Combining Deep and Shallow Approaches to Speculation Analysis

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Date: 21 April 2011

Venue: The Dialogue Systems Group
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Introduction

- Speculation Analysis = identifying uncertainty in text
- Increased interest from the NLP community recently:
  - The BioNLP 2009 Shared Task
  - The CoNLL 2010 Shared Task
  - The NeSp-NLP 2010 Workshop
  - A forthcoming special issue of Computational Linguistics

Some examples

BioScope Corpus

Biomedical texts with manual annotation of speculation **cues** (<>) and their corresponding **scope** ({}) (Vincze et al., 2008).

1. Second, {the interaction between roX RNA and MOF protein <appears> to lack specificity}.
2. These data {<indicate that> IL-10 and IL-4 inhibit cytokine production by different mechanisms}.
3. {The unknown amino acid <may> be used by these species}.

Outline

1. Data sets and evaluation measures
2. Identifying speculation cues
3. Resolving the scope of speculation
   - A rule-based approach using dependency structures
   - A data-driven approach using constituent structures
   - A hybrid approach
4. End-to-end evaluation and conclusions

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The BioScope corpus

The BioScope Data; Annotated for Speculation

		Speculation		
	Sentences	**Sentences**	**Cues**	**MW Cues**
BSA	11871	2101	2659	364
BSP	2670	519	668	84
BS	14541	2620	3327	448
BSE	5003	790	1033	87

Preprocessing

- BioScope XML converted to stand-off **characterisation**.
- Tokenisation performed using the GENIA tagger (Tsuruoka et al. 2005), supplemented with a cascaded finite-state tokeniser.
- Part-of-speech tags from both the GENIA tagger, for higher accuracy in the biomedical domain, and TnT (Brants 2000), in order to utilise the improved tokenisation.
- Dependency parsing using MaltParser (Nivre et al. 2006) **stacked** with the XLE platform (Crouch et al. 2008) with the English grammar developed by Butt et al. (2002).
- Constituent parsing with the HPSG-based *English Resource Grammar* (Flickinger 2002).

Evaluation measures

Evaluation was performed using the scoring software of the CoNLL 2010 Shared Task, with ten fold cross-validation.

$$\textbf{Prec} = \frac{\text{tp}}{\text{tp+fp}} \quad \textbf{Rec} = \frac{\text{tp}}{\text{tp+fn}} \quad \textbf{F1} = \frac{2\times\text{Prec}\times\text{Rec}}{\text{Prec+Rec}}$$

A true positive requires identification of **all words** in the cue/scope.

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Types of speculation cues

Farkas et al. (2010) note four types of speculation cues:

adjectives or adverbs	*probable*, *likely*, *possible*, *unsure*
auxiliaries	*may*, *might*, *could*
conjunctions	*either* . . . *or*
verbs	*suggest*, *suspect*, *indicate*, *suppose*

More than 85% of the cues observed in the BioScope corpus also occur as non-cues. For example:

1. In 5 patients the granulocytes {<appeared> polyclonal} [. . .]
2. The effect appeared within 30 min [. . .]

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2. The effect appeared within 30 min [...]

Our approach

We employ binary word-by-word (WbW) linear support vector machine classifiers using the SVM^{light} toolkit:

- using only surface unigrams (**Baseline**);
- using lemma trigrams left/right of, and bigrams to the right of the candidate word (*n*-**grams**); and
- disregarding candidate words that do not appear as cues in the training data (**Filtering**).

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Development results

Configuration Statistics for the Speculation Cue Classifiers

Model	# Examples	% Positives	# Features	# SVs
Baseline	340,000	1%	20,000	20,000
n-grams	340,000	1%	2,600,000	14,000
Filtering	10,000	30%	100,000	5,000

Identifying Speculation Cues

Model	Prec	Rec	F1
Baseline	90.49	81.16	85.57
n-grams	94.65	82.26	88.02
Filtering	94.13	84.60	89.11

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Error analysis

- False negative errors are most frequent (74%); of these, most are instances of high-frequency, high-ambiguity words:
  - the conjunction **or** (24%),
  - the modal **can** (10%),
  - the modal **could** (7%) and
  - the conjunction **either** (6%).
  - etc.
- 26% of errors are false positives; of these, 60% may be attributed to inaccurate annotation.

Held-out results

Identifying Speculation Cues

Model	Prec	Rec	F1
Baseline	75.15	72.39	74.70
n-grams	**86.33**	74.21	79.82
Filtering	84.79	77.17	80.80
Tang et al. 2010	81.70	**80.99**	**81.34**

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Scope resolution rules

The scope of a speculation depends on the linguistic properties of the cue (Vincze et al. 2008).

- **Coordinations** scope over their conjuncts;
- **Prepositions** scope over their arguments with its descendants;
- **Attributive adjectives** scope over their nominal head and its descendants;
- **Predicative adjectives** scope over referential subjects and clausal arguments, if present;

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Scope resolution rules

- **Modals** inherit subject scope from their lexical verb and scope over their descendants;
- **Passive verbs** scope over referential subjects and the verbal descendants;
- **Raising verbs** scope over referential subjects and the verbal descendants; *else*
- the **Default** scope is applied by labeling from the cue to the final punctuation.

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Evaluating the scope resolution rules

Speculation Scope for Gold Cues

Data	Configuration	F1
BSA	Default Baseline	69.84
	Dependency Rules	73.67
BSP	Default Baseline	45.21
	Dependency Rules	72.31
BSE	Default Baseline	46.95
	Dependency Rules	66.73

Error analysis

When using gold cues in **BSP**, the dependency rules generate errors in 27.7% of cases. Of these, most are:

- either parsing errors leading to incorrect phrase and clause boundaries, for example:

  [. . .] {the reverse complement mR of m will be <considered> to be [. . .]}

- or, adverbials of condition, reason or contrast attaching to cues in a dependency analysis, but not being included in the scope annotation, for example:

  This {<might> affect the results} if there is a systematic bias [. . .]

Other errors arise from inaccurate annotation or inclusion of parenthesised elements such as citations.

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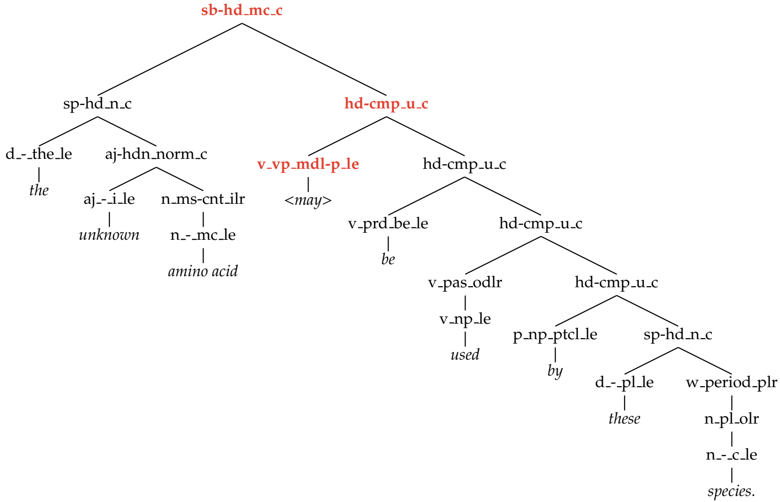
Data-driven scope resolution

Select from candidate scopes on the basis of constitutent trees.



Our approach

Learn a ranking function over candidate constituents within a parse (or parses).

Candidates are generated by following the path from the cue to the root of the tree, for example:

- **modal verb** : [24, 27] : `False`
  The unknown amino acid {<may>} by used by these species.
- **head – complement** : [24, 52] : `False`
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- **subject – head** : [0, 52] : `True`
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Alignment of constituents and scopes

Scope boundaries must align with the boundaries of constituents for the approach to be successful.

Alignment can be improved by applying **slackening** rules, including:

- eliminating constituent-final punctuation;
- eliminating constituent-final parenthesised elements;
- reducing scope to the left when the left-most terminal is an adverb and not the cue; and
- ensuring the scope starts with the cue when it is a noun.

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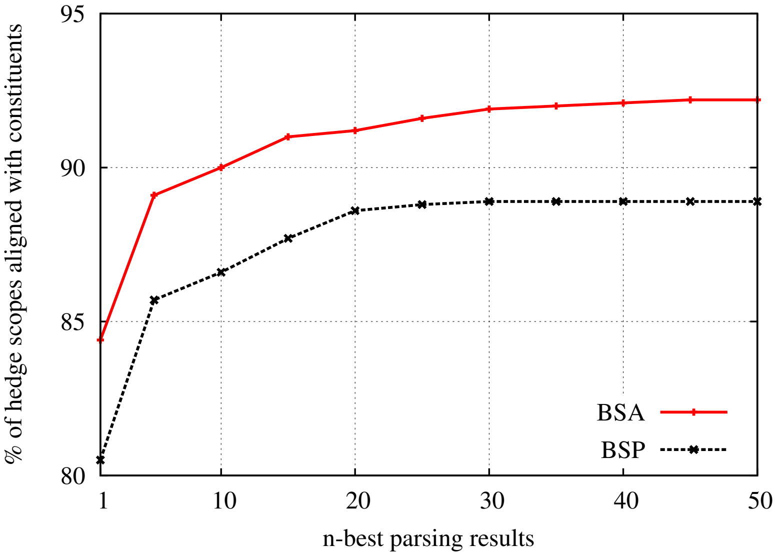

Alignment of constituents and scopes

Analysis of the non-aligned items indicated that mismatches arise from:

- parse ranking errors (40%),
- non-syntactic scope (25%),
- divergent syntactic theories (16%),
- parenthesised elements (13%) and
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Alignment when inspecting the first parse in **BSP** is 80.5%. Given an observed parser coverage of 85.6%, the **upper-bound accuracy** of the ranker on **BSP** is around 76%.

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Candidate features

- **Path** features:
  - Lexicalised and unlexicalised paths from speculation cues to candidate constituents:
    - specific (e.g. `v_vp_mdl-p_le\hd-cmp_u_c\sb-hd_mc_c`)
    - general (e.g. `v_vp_mdl-p_le\\sb-hd_mc_c`)
  - Bigrams formed of nodes and their parents
- **Surface** features:
  - Bigrams formed of preterminal lexical types
  - Cue position within candidate (in tertiles)
  - Candidate size relative to sentence length (in quartiles)
  - Punctuation preceeding the candidate
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- **Linguistic** features:
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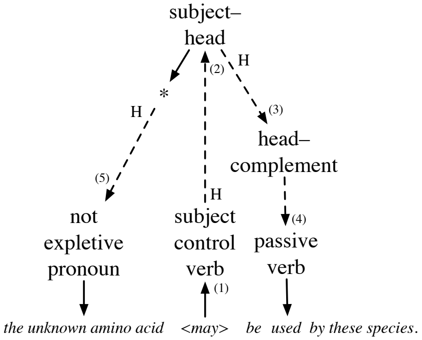
Detecting control verbs with a passivised verb

1. Cue is a subject control verb.
2. Find the first subject – head parent of (1) on the head path.
3. Find the first head – complement child of (2) on the head path.
4. The right-most daughter of (3) or one of its descendents is a passivized verb.
5. The transitive head daughter of the left-most daughter of (2) is not an expletive *it* or *there*.



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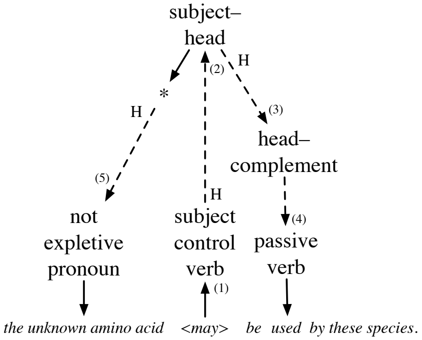

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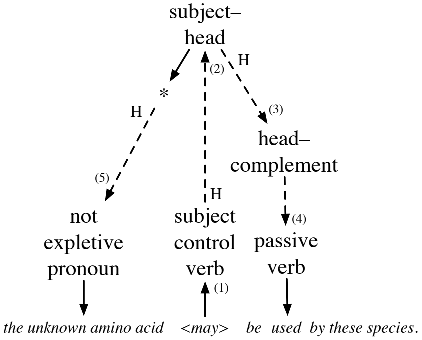

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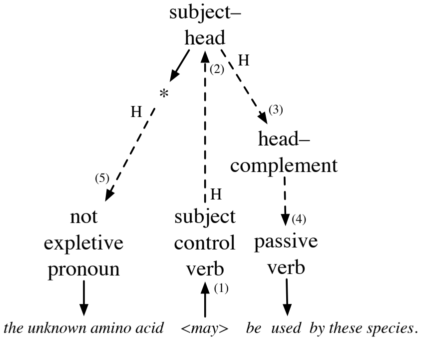

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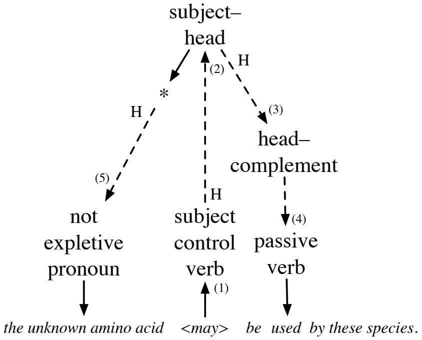

Ranker optimisation

Ranker Optimization on BSP

Features	Aligned	Parsed
Baseline	26.76	22.39
Path	78.10	65.80
Path+Surface	79.93	67.25
Path+Linguistic	83.72	70.47
Path+Surface+Linguistic	85.30	71.63

Training with the first aligned constituent in n-best parses and testing with m-best parses did not greatly impact performance, but optimal values are: $n = 1$ and $m = 3$.

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Evaluating the ranker

Speculation Scope for Gold Cues

Data	Configuration	F1
BSA	Default	69.84
	Dependency Rules	73.67
	Constituent Ranker	75.56
BSP	Default	45.21
	Dependency Rules	72.31
	Constituent Ranker	66.32
BSE	Default	46.95
	Dependency Rules	66.73
	Constituent Ranker	59.15

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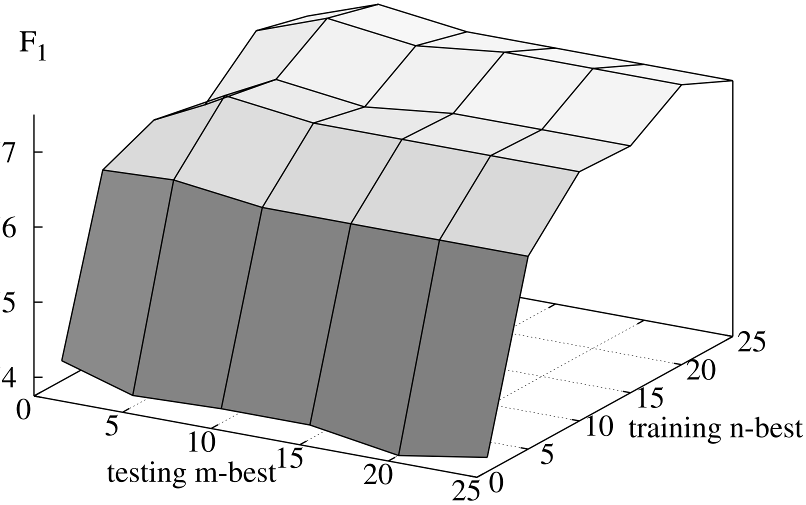
Combining the rules with the ranker

- Combining the rules with the ranker is possible if an ERG parse is available
- In these cases we introduce a dependency-rules prediction feature, attached to the standard path features
- In other cases we stick with the rules' prediction

n-best optimisation



Evaluating the combined approach

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End-to-end development results

Scope Resolution on Predicted Cues

Data Set	Configuration	Prec	Rec	F1
BSA	Rules	72.47	66.42	69.31
	Ranker	74.23	68.03	71.00
	Combined	77.60	71.12	74.22
BSP	Rules	69.87	62.13	65.77
	Ranker	62.96	55.99	59.27
	Combined	71.38	63.47	67.20

Final evaluation

Final End-to-End Results on BSE

	Scope Level		
System	**Prec**	**Rec**	**F1**
Our approach	61.47	56.53	58.90
Morante et al. 2010	59.62	55.18	57.32

Conclusions

- Speculation can be identified by making a **closed-class** assumption, and using a linear SVM classifier to disambiguate known speculation cues;
- **Linguistically-motivated heuristics** over automatically-parsed dependency structures are effective in determining the scope of speculations;
- It is possible to learn a **discriminative ranking function** for choosing subtrees from HPSG-based constituent structures that match speculation scopes; and
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