

SDP 2014 (SemEval Task 8)

Broad-Coverage Semantic Dependency Parsing

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By Way of Introduction: Semantic Dependencies

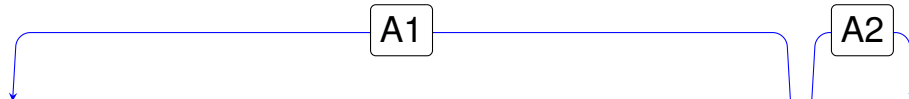
A similar technique is almost impossible to apply to other crops .

The diagram illustrates semantic dependencies between two phrases in the sentence. A1 is positioned above 'A similar technique' and A2 is positioned above 'to other crops'. A horizontal line connects A1 and A2, with a downward arrow pointing to 'A similar technique' and another downward arrow pointing to 'to other crops', indicating a dependency between these two parts of the sentence.

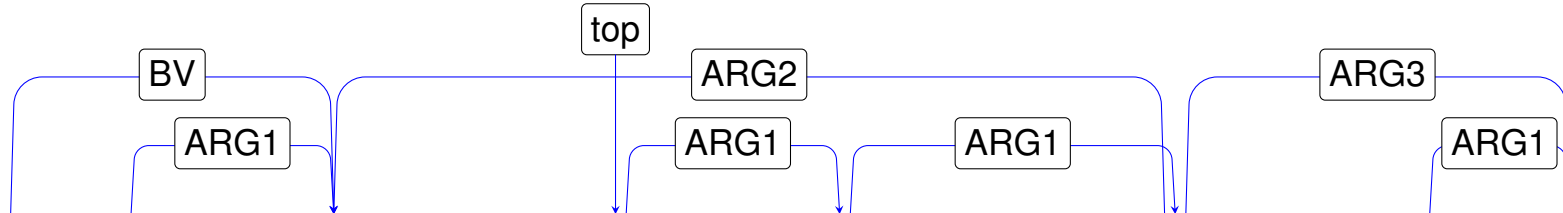


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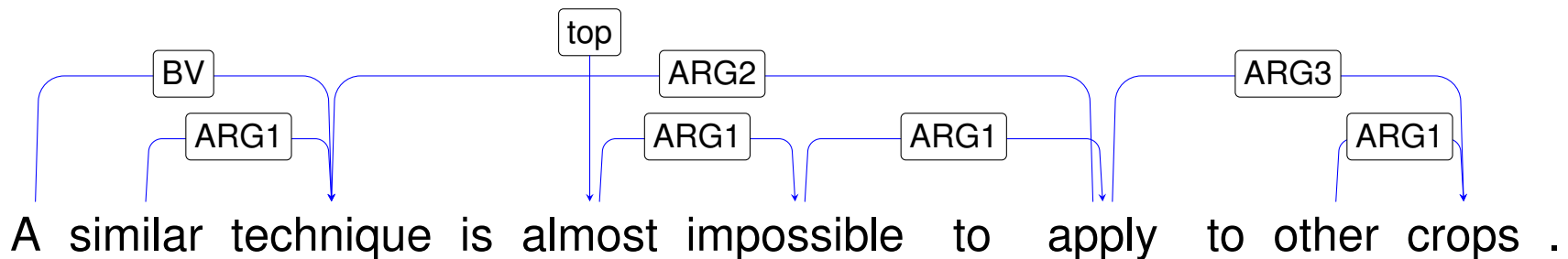
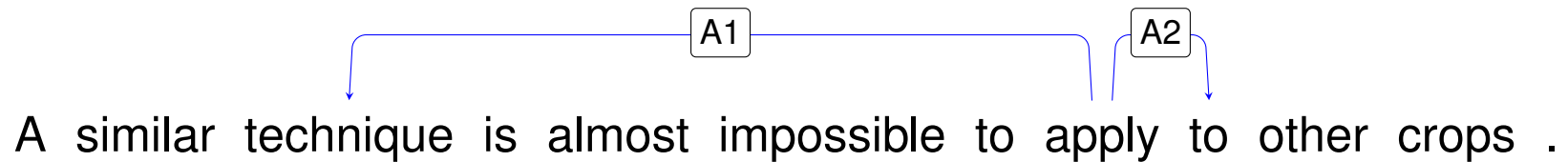
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By Way of Introduction: Semantic Dependencies



High-Level Linguistic and Formal Properties

- Core *semantic* predicate–argument structure, or ‘Who did What to Whom?’
- argument sharing: graph re-entrancies; vacuous words: unattached nodes;
- designated *top* node (not root): semantic head, highest-scoping predicate.



Task Definition, Goals, and High Hopes

We define BROAD-COVERAGE SEMANTIC DEPENDENCY PARSING (SDP) as the task of recovering sentence-internal predicate–argument relationships for ALL CONTENT WORDS, i.e. the semantic structure constituting the relational core of sentence meaning.

[2014 Task Description]



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[2014 Task Description]

Push Dependency Parsing Towards Directed Graphs

- Higher degree of abstraction: deep syntax or predicate–argument structure;
- e.g. shared arguments (control, relative clauses); vacuous word classes.

Define ‘Semantic Role Labeling’ for All Content Words

- Argument labeling for phenomena like negation, comparatives, possessives.



Three Parallel Annotations of the WSJ Corpus

DM: DELPH-IN MRS-Derived Bi-Lexical Dependencies

- DeepBank: Fresh HPSG-style annotation, including logical-form semantics;
- ‘lossy’ reduction of MRS meaning representations to bi-lexical dependencies.



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PAS: Enju Predicate–Argument Structures

- Enju Treebank: Projection of (complete) PTB syntax to HPSG derivations;
- semantic analyses take form of lexicalized predicate–argument structures.



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PCEDT: Parts of the Prague Tectogrammatical Layer

- Include all nodes from Prague t-trees that correspond to surface tokens;
- re-attach functors of generated nodes; project dependencies to conjuncts.



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Sections 00–20 for Training (745,543 Tokens); Section 21 for Testing (29,808).



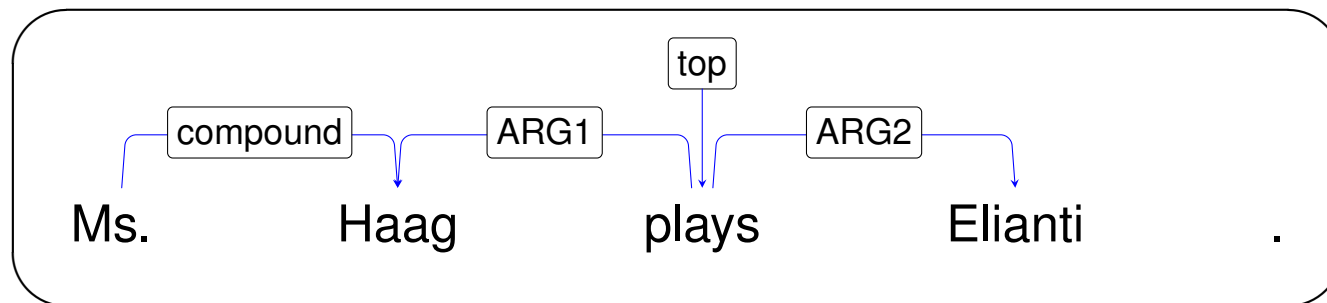
Token-Oriented, Tabular Data Format

<i>id</i>	<i>form</i>	<i>lemma</i>	<i>pos</i>	<i>top</i>	<i>pred</i>	<i>arg1</i>	<i>arg2</i>
#20200002							
1	Ms.	Ms.	NNP	—	+	—	—
2	Haag	Haag	NNP	—	—	compound	ARG1
3	plays	play	VBZ	+	+	—	—
4	Elianti	Elianti	NNP	—	—	—	ARG2
5	.	.	.	—	—	—	—



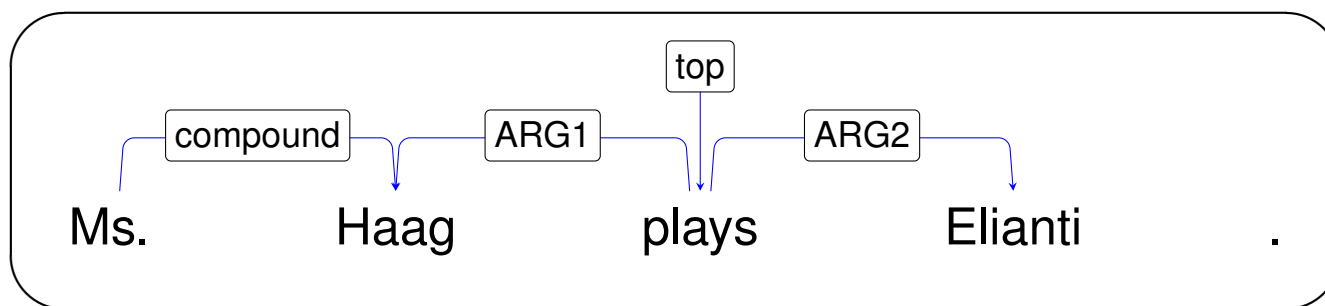
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5	.	.	.	-	-	-	-



- Sub-set of fields from CoNLL 2009; simplified `pred` column, added `top`;
→ generic data format: labeled directed graphs with designated top node(s).



Quantitative Comparison of Target Representations

		DM	PAS	PCEDT
(1)	# labels	51	42	68
(2)	% singletons	22.62	4.49	35.79
(3)	# edge density	0.96	1.02	0.99
(4)	%_g trees	2.35	1.30	56.58
(5)	%_g projective	3.05	1.71	53.29
(6)	%_g fragmented	6.71	0.23	0.56
(7)	%_n reentrancies	27.35	29.40	9.27
(8)	%_g topless	0.28	0.02	0.00
(9)	# top nodes	0.9972	0.9998	1.1237
(10)	%_n non-top roots	44.71	55.92	4.36



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- PCEDT is most fine-grained in labels (1); also most 'tree-like' (4, 7, 10);
- PAS is most 'covering' (2) and most connected (3; ignoring singletons);
- DM has some structural red flags: fragmented and topless graphs (6, 8).



Pairwise Similarity (Unlabeled Dependency F_1)

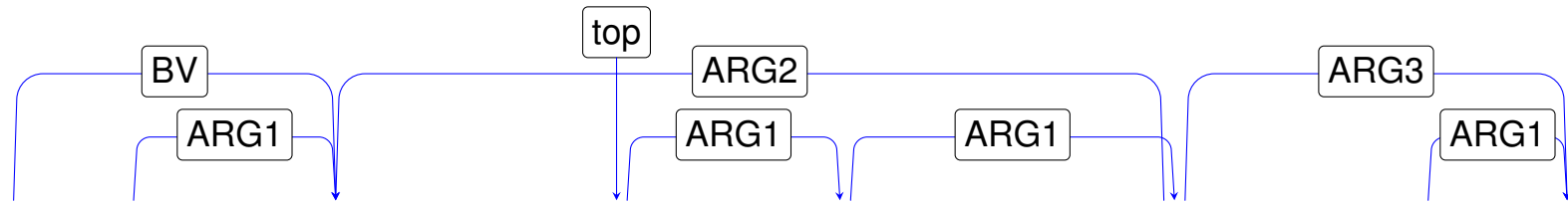
	Directed			Undirected		
	DM	PAS	PCEDT	DM	PAS	PCEDT
DM	—	.6425	.2612	—	.6719	.5675
PAS	.6688	—	.2963	.6993	—	.5490
PCEDT	.2636	.2963	—	.5743	.5630	—

(Upper Right Diagonals: Including punctuation; Lower Left: Ignoring It)

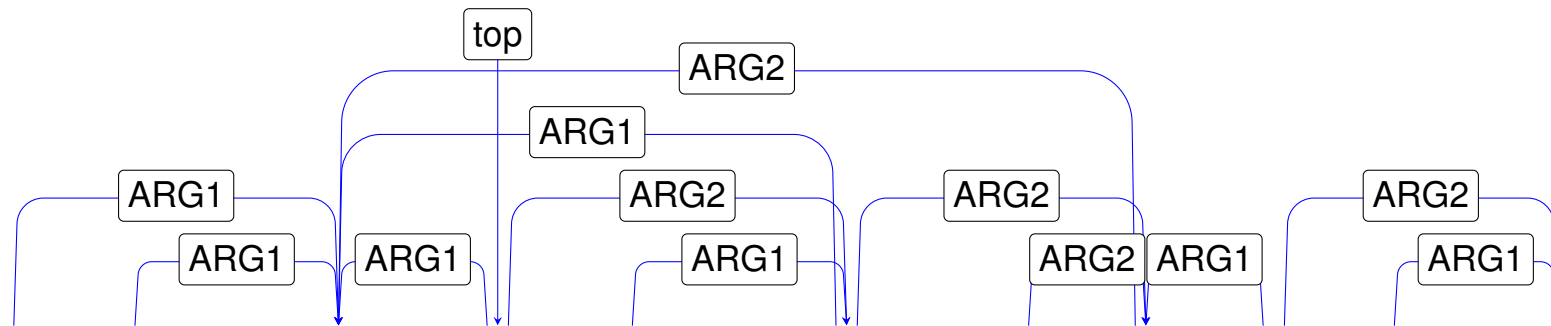
- DM and PAS structurally much closer to each other than either to PCEDT;
- effect stronger when ignoring dependencies involving punctuation marks;
- directionality of dependencies one of the major sources of divergence.



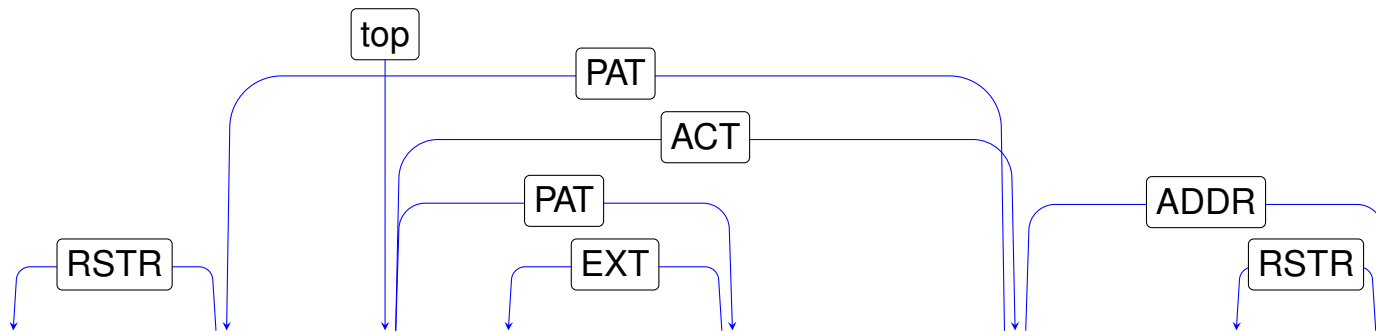
Linguistic Comparison of Target Representations



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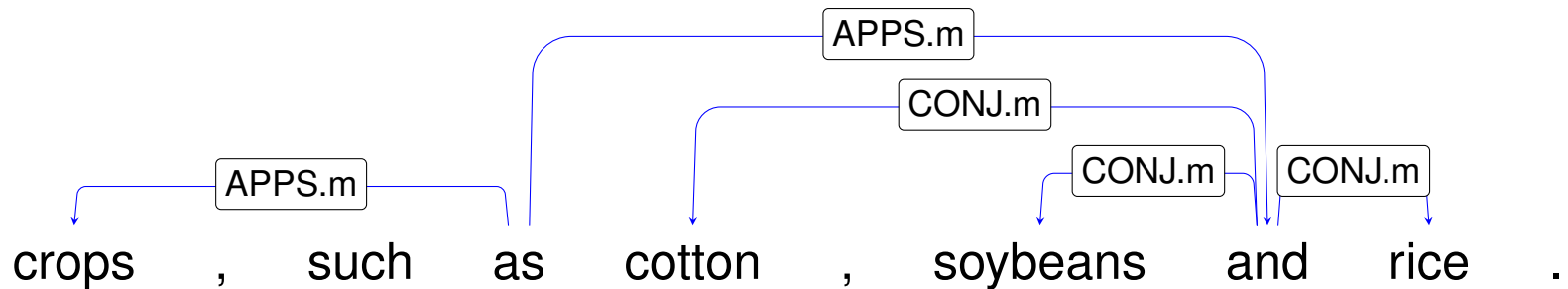
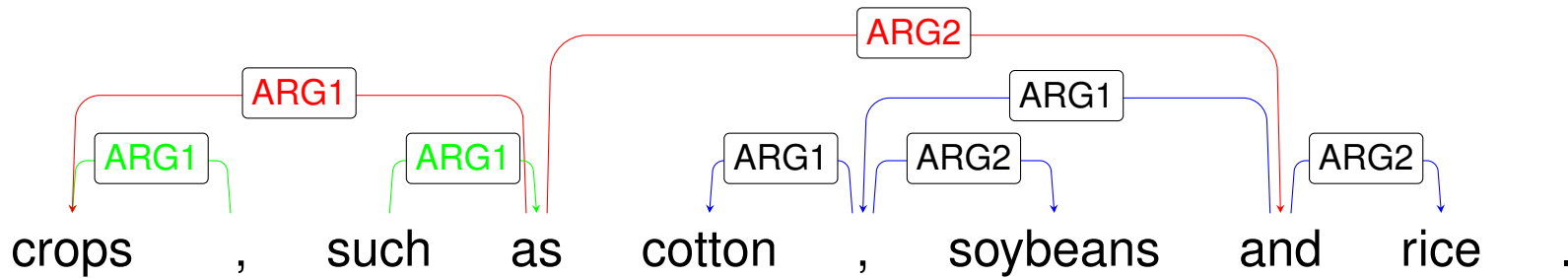
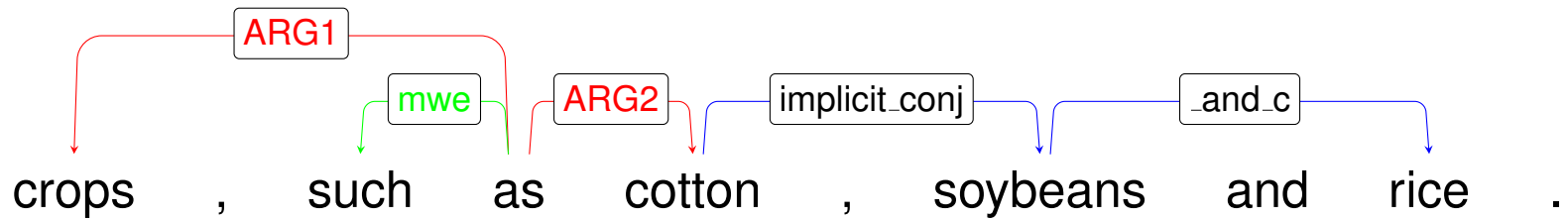
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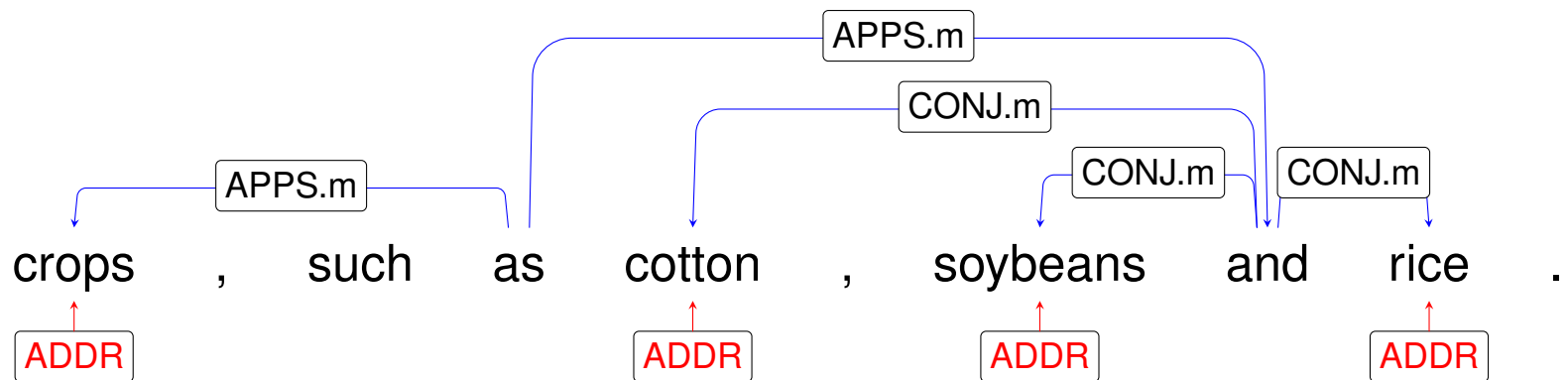
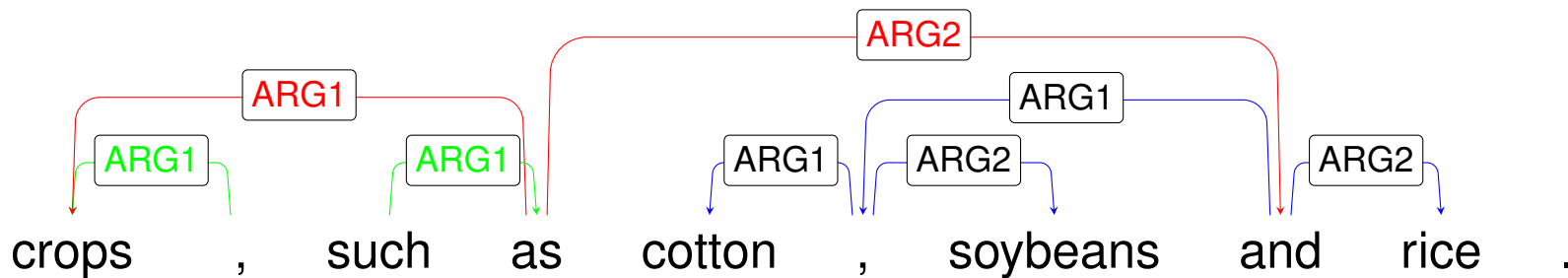
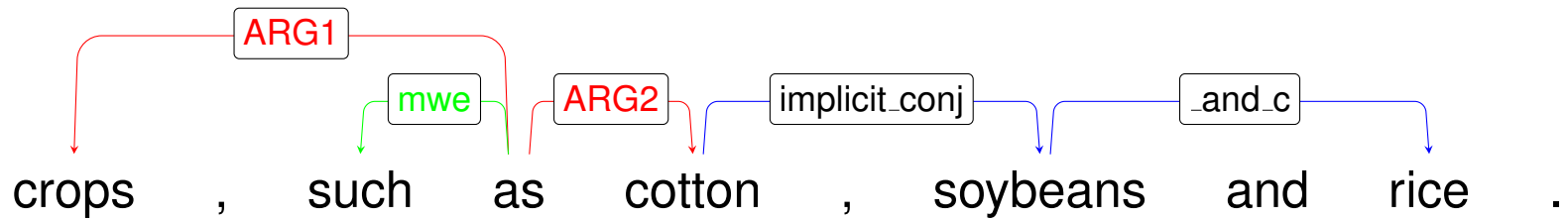
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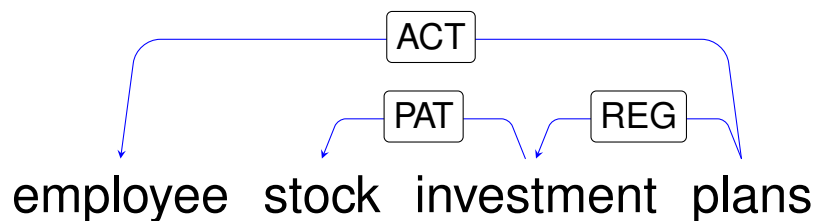
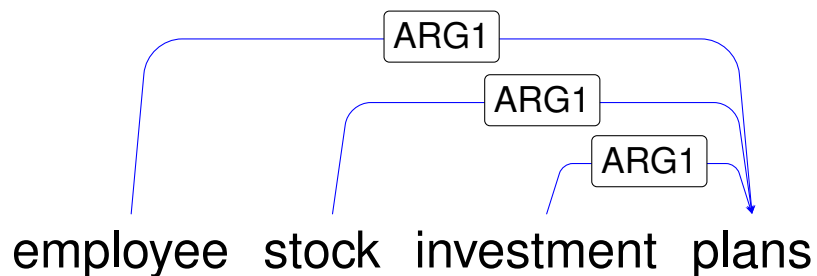
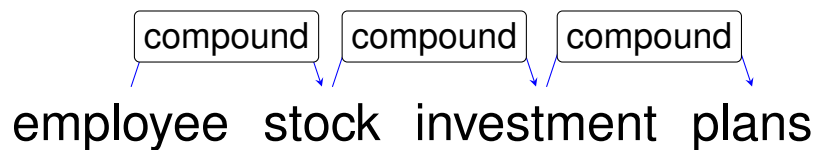
Different Approaches to Coordinate Structures



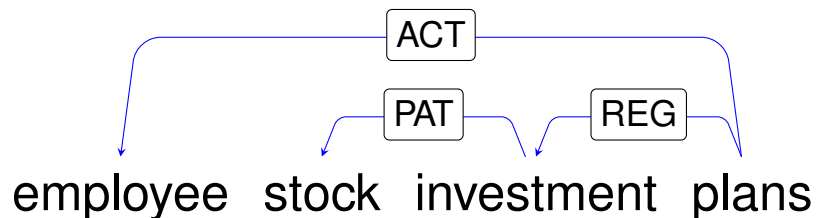
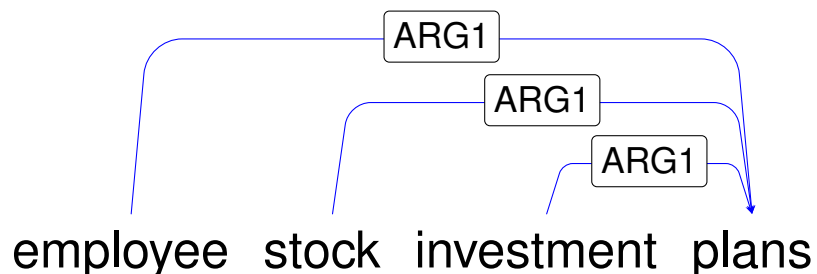
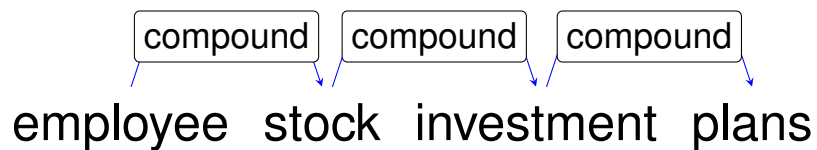
Different Approaches to Coordinate Structures



Diverging Ambitions: Sentence vs. Speaker Meaning



Diverging Ambiguities: Sentence vs. Speaker Meaning



- ? Meaning determined by linguistic signal alone vs. by utterance context;
- internal bracketing arguably grammaticalized, but not role interpretation.



Task Setup

Evaluation Metrics

- Labeled and unlabeled precision, recall, and F_1 of individual dependencies;
- additionally, labeled and unlabeled exact sentence accuracy (much stricter);
- identification of *top* node(s) considered additional, ‘virtual’ dependencies.

Closed vs. Open Tracks

- Beyond lemma and part of speech, no representation of syntax in Task data;
- investigate role of syntax in separate, ‘open’ track: (almost) no holds barred;
- ‘companion’ analyses: simplified PTB phrase structure and Stanford Basic.



Participating Teams and Approaches

Team	Track	Approach	Resources
Alpage	C & O	transition-based parsing for DAGs, logistic regression, structured perceptron	companion, Brown clusters
CMU	O	edge classification by logistic regression, edge-factored structured SVM	companion
Copenhagen-Malmö	C	graph-to-tree transformation, Mate	—
In-House	O	pre-existing parsers developed by the organizers	grammars
Linköping	C	extension of Eisner's algorithm for DAGs, edge-factored structured perceptron	—
Peking	C	transition-based parsing for DAGs, graph-to-tree transformation, parser ensemble	—
Potsdam	C & O	graph-to-tree transformation, Mate	companion
Priberam	C & O	model with second-order features, decoding with dual decomposition, MIRA	companion
Turku	O	cascade of SVM classifiers (dependency recognition, label classification, top recognition)	companion, syntactic n-grams, word2vec



Official Results: ‘Closed’ and ‘Open’ Tracks

	DM					PAS				PCEDT			
	\overline{LF}	LP	LR	LF	LM	LP	LR	LF	LM	LP	LR	LF	LM
Peking	85.91	90.27	88.54	89.40	26.71	93.44	90.69	92.04	38.13	78.75	73.96	76.28	11.05
Priberam	85.24	88.82	87.35	88.08	22.40	91.95	89.92	90.93	32.64	78.80	74.70	76.70	09.42
Copenhagen- Malmö	80.77	84.78	84.04	84.41	20.33	87.69	88.37	88.03	10.16	71.15	68.65	69.88	08.01
Potsdam	77.34	79.36	79.34	79.35	07.57	88.15	81.60	84.75	06.53	69.68	66.25	67.92	05.19
Alpage	76.76	79.42	77.24	78.32	09.72	85.65	82.71	84.16	17.95	70.53	65.28	67.81	06.82
Linköping	72.20	78.54	78.05	78.29	06.08	76.16	75.55	75.85	01.19	60.66	64.35	62.45	04.01



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	\overline{LF}	LP	LR	LF	LM	LP	LR	LF	LM	LP	LR	LF	LM
Priberam	86.27	90.23	88.11	89.16	26.85	92.56	90.97	91.76	37.83	80.14	75.79	77.90	10.68
CMU	82.42	84.46	83.48	83.97	08.75	90.78	88.51	89.63	26.04	76.81	70.72	73.64	07.12
Turku	80.49	80.94	82.14	81.53	08.23	87.33	87.76	87.54	17.21	72.42	72.37	72.40	06.82
Potsdam	78.60	81.32	80.91	81.11	09.05	89.41	82.61	85.88	07.49	70.35	67.33	68.80	05.42
Alpage	78.54	83.46	79.55	81.46	10.76	87.23	82.82	84.97	15.43	70.98	67.51	69.20	06.60
In-House	75.89	92.58	92.34	92.46	48.07	92.09	92.02	92.06	43.84	40.89	45.67	43.15	00.30



Outlook: Candidate Revisions for SDP 2015

Out-of-Domain Testing

?

Complete-Predicate Scoring

?

Harmonization of Target Representations

?

Cross-Linguistic Variation

?

Predicate Disambiguation

?

