Rhetorical structure and argumentation structure in monologue text

Andreas Peldszus   Manfred Stede

Applied Computational Linguistics, University of Potsdam

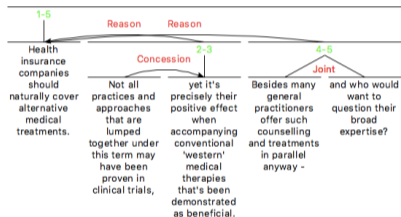3rd Workshop on Argument Mining @ACL 2016, Berlin, 12.08.2016

Outline

1. Introduction

2. Matching RST and argumentation: Qualitative analysis

3. Automatically deriving ARG from RST

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1 Introduction

2 Matching RST and argumentation: Qualitative analysis

**3** Automatically deriving ARG from RST

RST in a nutshell

Health insurance companies should naturally cover alternative medical treatments.

Not all practices and approaches that are lumped together under this term may have been proven in clinical trials,

yet it's precisely their positive effect when accompanying conventional 'western' medical therapies that's been demonstrated as beneficial.

Besides many general practitioners offer such counselling and treatments in parallel anyway –

and who would want to question their broad expertise?

Key ideas and principles [Mann and Thompson, 1988]

- text coherent <=> a plausible RST tree exists
- 25 relations: presentational (pragmatic) vs. subject-matter (semantic)
- most relations: nucleus (main info/act) + satellite (support info/act)
- same relation set applies to minimal units and recursively to text spans
- every unit/span takes part in the analysis
- no crossing edges
- (annotation guidelines in [Stede, 2016])

Argumentation structure in a nutshell
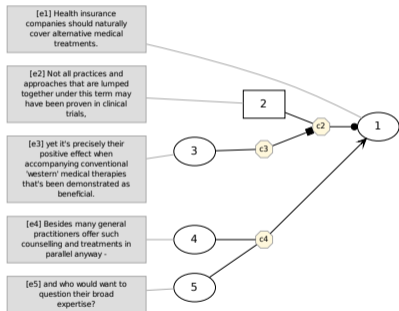
Freeman's theory, revised & slightly generalized:

[Freeman, 1991, 2011] [Peldszus and Stede, 2013]

- node types = *argumentative role*
  proponent (presents and defends claims)
  opponent (critically questions)
- link types = *argumentative function*
  support own claims (normally, by example)
  attack other's claims (rebut, undercut)
- (annotation guidelines in [Stede, 2016])

Outline

Dataset: argumentative microtexts

Properties:

- about 5 segments long
- each segment is arg. relevant
- explicit main claim
- at least one possible objection considered

Texts:

- 23 texts: hand-crafted, covering different arg. configurations
- 92 texts: collected in a controlled text generation experiment
- with professional parallel translation to English
- all annotated with argumentation structure
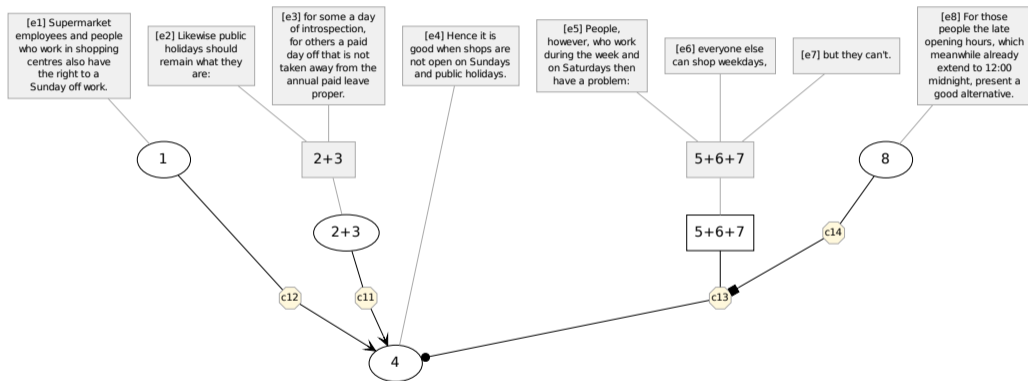- freely available, CC-by-nc-sa license; see [Peldszus and Stede, 2016]

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Multi-layer discourse annotation

How does argumentation structure relate to other discourse structures?

- Rhetorical Structure Theory (RST)
  [Mann and Thompson, 1988]
- Segmented Discourse Structure Theory (SDRT)
  [Asher and Lascarides, 2003]

Joint work with Stergos Afantenos, Nicholas Asher, Jérémy Perret
[Stede et al., 2016]

Multi-layer discourse annotation: Harmonize segmentation

[e1] Supermarket employees and people who work in shopping centres also have the right to a Sunday off work.

[e2] Likewise public holidays should remain what they are:

[e3] for some a day of introspection, for others a paid day off that is not taken away from the annual paid leave proper.

[e4] Hence it is good when shops are not open on Sundays and public holidays.

[e5] People, however, who work during the week and on Saturdays then have a problem:

[e6] everyone else can shop weekdays,

[e7] but they can't.

[e8] For those people the late opening hours, which meanwhile already extend to 12:00 midnight, present a good alternative.

Qualitative: Central Claim

Total: 115 CCs in ARG (one per text)

- *Canonical:* In 95 texts (85%), central nucleus in RST corresponds to central claim in ARG
- In 5 texts, they are disjoint
    - multiple statements of the CC
    - no explicit CC
- In 12 texts, they overlap
    - ARG CC has more fine-grained RST analysis (e.g., Condition)
    - multinuclear RST relations yield multiple RSTnuc for the text

Qualitative: Support

Total: 261 Support relations in ARG

- *Canonical:* 132 correspond to RST Reason, Justify, Evidence, Motivation, Cause
- But: 77% of the texts contain at least one non-canonical Support
- 12 Supports correspond to another (mostly 'informational') RST relation
- 117 Supports have no corresponding RST relation
    - RST segment is in a multinuclear relation (70)
    - RST segment is related to a different segment via an informational relation (21)
    - Mismatch in Support transitivity (16)
    - Other (18)

Qualitative: Attack

Total: 98 Attack relations in ARG

- Simple: A single attacking node (either leaf or supported)
  - *Canonical:* (24/31) Attack corresponds to Antithesis, Contrast, Concession
  - (7/31) opponent voice absent in RST, or segment connected otherwise

- Medium: Multiple individual attacks in ARG
  - *Canonical:* In all 7 cases, RST groups them via Conjunction

- Complex: Attack and Counterattack
  - *Canonical:* (47/60) Attack corresponds to a backward Concession, Antithesis (different levels of complexity)
 - (13/60) Annotator did not see this argumentative function as primary

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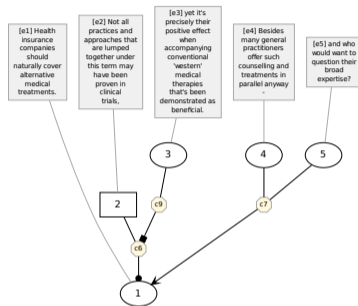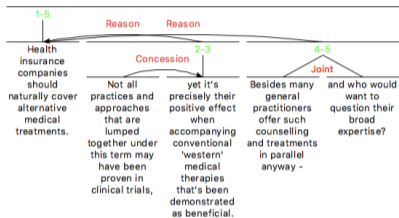
Task

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Common dependency format [Stede et al., 2016]

Evaluation procedure

Evaluate four aspects of the predicted structure:

- **central claim (cc):** [yes, no]
- **role (ro):** [proponent, opponent]
- **function (fu):** [support, example, rebut, undercut, link, join]
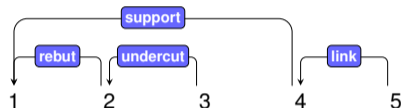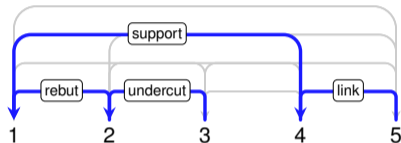- **attachment (at):** [yes, no]

Procedure and train/test splits as in [Peldszus and Stede, 2015]

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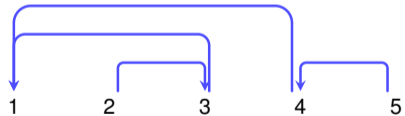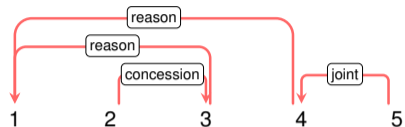Evaluate four aspects of the predicted structure:

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Model 1: Heuristic baseline (BL)

Procedure:

1. predict ARG structure isomorphic to RST tree
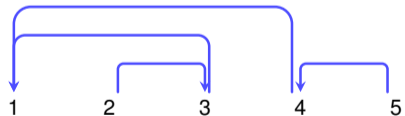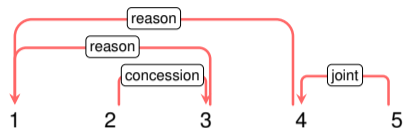2. map RST relations to ARG relation
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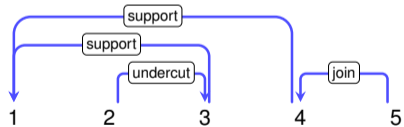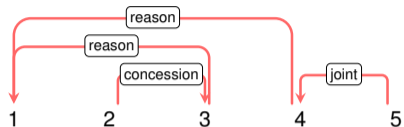   best correlation according to [Stede et al., 2016]

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support: background, cause, evidence, justify, list, motivation, reason, restatement, result
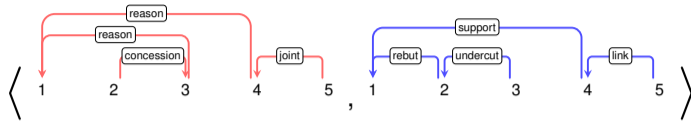**rebut**: antithesis, contrast, unless
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join: circumstance, condition, conjunction, disjunction, e-elaboration, elaboration, evaluation-s, evaluation-n, interpretation*, joint, means, preparation, purpose, sameunit, solutionhood*
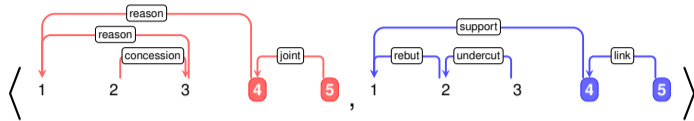

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Model 2: Naive aligner (A)

Training procedure:

1. find common connected components

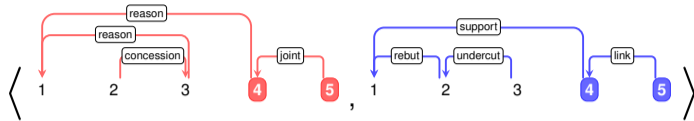2. extract corresponding subgraphs

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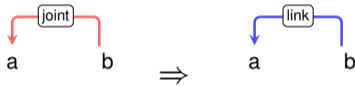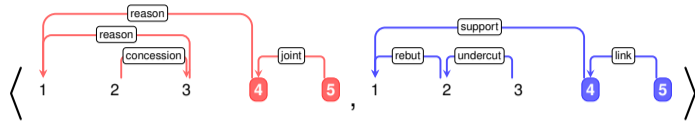
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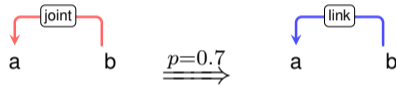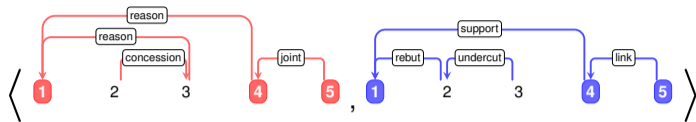2. extract corresponding subgraphs
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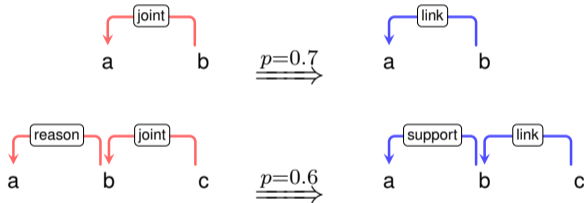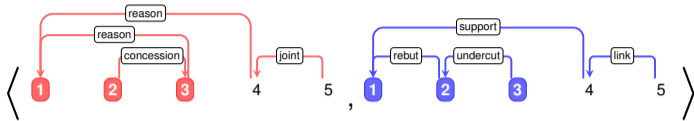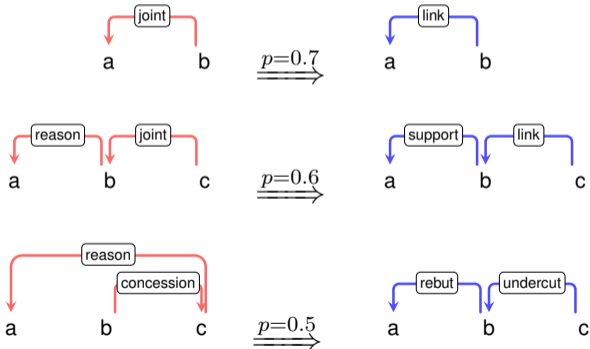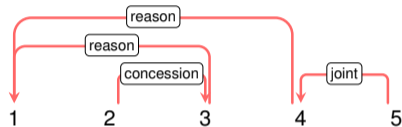2. extract corresponding subgraphs
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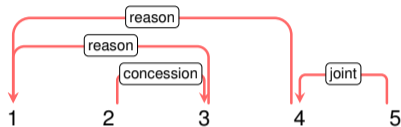
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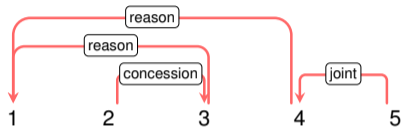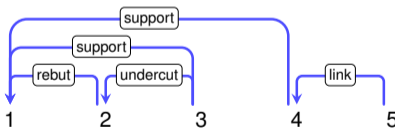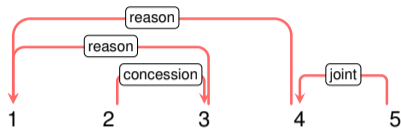
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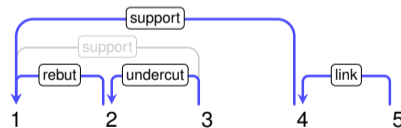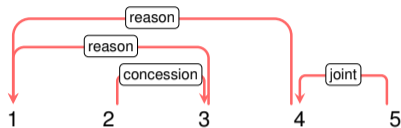   [Chu and Liu, 1965, Edmonds, 1967]
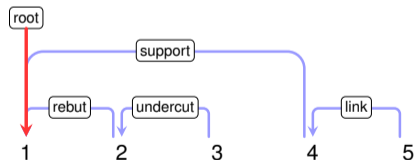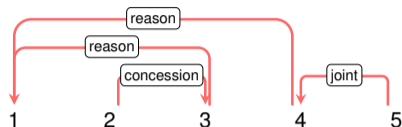
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Model 3: Evidence graph (EG)

Evidence graph model [Peldszus and Stede, 2015]:

- train one base classifier for each of the 4 levels (cc, ro, fu, at)

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- base features incl. 2-node subgraph features:
    - position of the segment in the text
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    - number of incoming/outgoing edges
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- 3-node subgraph features
    - all relation chains of length 2 involving this segment
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Segment-pair features:

- direction of the potential link (forward or backward)
- distance between the segments
- whether there is an edge between the segments
- type of the edge between the segments or None

Results

scores reported as macro avg. F1

model	cc	ro	fu	at	unknown

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A-2	.578	.599	.314	.650	10.6%
A-23	.787	.744	.398	.707	7.5%
A-234	.797	.755	.416	.719	7.0%
A-2345	.794	.762	.424	.721	6.8%

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A-2+r	.861	.681	.385	.682	13.9%
A-23+r	.861	.783	.420	.716	11.3%
A-234+r	.861	.794	.434	.723	10.8%
A-2345+r	.861	.800	.443	.725	10.7%

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A-234+r	.861	.794	.434	.723	10.8%
A-2345+r	.861	.800	.443	.725	10.7%
EG-2	.918	.843	.522	.744	
EG-23	**.919**	.869	.526	**.755**	
EG-234	.918	.868	**.530**	.754	

Conclusions & Outlook

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- first *empirical study* on the relationship between RST and ARG
  - majority of mappings canonical
  - tension between intentional and informational analysis in RST
- *automatically mapping* RST to ARG
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Outlook:

- similar empirical analysis with longer text
- try using RST parser output
- augment arg mining text pipeline with RST features

Literatur I

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Y. J. Chu and T. H. Liu. On the shortest arborescence of a directed graph. *Science Sinica*, 14:1396–1400, 1965.

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