

Parallel Discourse Annotations on a Corpus of Short Texts

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Abstract

We present the first corpus of texts annotated with two alternative approaches to discourse structure, Rhetorical Structure Theory (Mann and Thompson, 1988) and Segmented Discourse Representation Theory (Asher and Lascarides, 2003). 112 short argumentative texts have been analyzed according to these two theories. Furthermore, in previous work, the same texts have already been annotated for their argumentation structure, according to the scheme of Peldszus and Stede (2013). This corpus therefore enables studies of correlations between the two accounts of discourse structure, and between discourse and argumentation. We converted the three annotation formats to a common dependency tree format that enables to compare the structures, and we describe some initial findings.

Keywords: Discourse structure, Argumentation, Multi-layer annotation

1. Introduction

In recent years, three approaches to analyzing and representing discourse structure have resulted in various annotated corpora and in implemented discourse parsers:

- The Penn Discourse Treebank (PDTB) annotates individual connectives with their coherence relations and their argument spans (Prasad et al., 2008).
- Rhetorical Structure Theory (RST) predicts tree structures on the grounds of underlying coherence relations that are mostly defined in terms of speaker intentions (Mann and Thompson, 1988).
- Segmented Discourse Representation Theory (SDRT) exploits graphs to model discourse structures and defines coherence relations via their semantic effects on commitments rather than relative to speaker intentions (Asher and Lascarides, 2003; Lascarides and Asher, 2009).

Of these, only RST and SDRT aim at predicting a full discourse structure, and our concern in this paper is with these two theories. To date, it has been difficult to compare the two accounts on empirical grounds, since there were no directly-comparable parallel annotations of the same texts. To improve on this situation, we took an existing corpus of 112 short “microtexts”, which had already been annotated with argumentation structure, and added layers for RST and SDRT. To this end, we harmonized the underlying segmentation rules for minimal discourse units, so that the resulting structures can be compared straightforwardly. We implemented an approach to merging the annotations and report here on some initial observations on the correlations between RST, SDRT and argumentation in that corpus.

In addition to comparing RST and SDRT, we foresee interesting applications of this kind of corpus data for purposes of argumentation mining. The correlations between discourse structure and argumentation structure have not been studied yet in depth, and thus it is not clear whether established discourse parsing techniques (geared either toward RST or toward SDRT) can contribute to an automatic argumentation analysis, and if so, in what ways.

In the following, we introduce our data set (Section 2.) and briefly describe the three layers of annotation (Sections 3.-6.). Then, we explain the mapping of the layers to a common dependency tree format, and we present some initial observations on correlations. (Section 7.). Finally, Section 8. gives an outlook on potential future work.

2. Data

The “corpus of argumentative microtexts” (Peldszus and Stede, to appear) has been designed as a collection of relatively “simple” yet authentic texts that allow for studying the mechanics of argumentation. It consists of two parts: On the one hand, 23 texts were written by one of the authors and have been used as examples in teaching and testing argumentation analysis with students. On the other hand, 90 texts have been collected in a controlled text generation experiment, where 23 subjects wrote short texts of controlled linguistic and rhetoric complexity, discussing one of the issues they chose from a pre-defined list of controversial issues. These include questions like “Should everybody be required to pay fees for public radio and TV” or “Should health insurers cover alternative medical treatments”.

Each text was to fulfill three requirements: It should be about five segments long; all segments should be argumentatively relevant, either formulating the main claim of the text, supporting the main claim or another segment, or attacking the main claim or another segment. Also, the probands were asked that at least one possible objection to the claim should be considered in the text.

To supplement the original German version of the collected texts, the whole corpus has been professionally translated to English. Figure 1 shows a sample text from this English part of the corpus. A more detailed overview of the data collection is given in (Peldszus and Stede, to appear). For the purposes of this study, we worked with the English version of the corpus. The finer EDU segmentation as well as the creation of the additional RST and SDRT annotation layers was done on the basis of the English text. Mapping the new annotations back to the German version of corpus is future work. The corpus is freely available online.¹

¹For the original German/English corpus, see <https://>

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?

Figure 1: Sample text from Microtext Corpus

3. Argumentation structure

The initial release of the corpus already incorporated argumentation structures for all texts, following the scheme devised in Peldszus and Stede (2013), which itself is based on Freeman's theory of the macro-structure of argumentation (Freeman, 1991; Freeman, 2011). Its central idea is to model argumentation as a hypothetical dialectical exchange between the *proponent*, who presents and defends his claims, and the *opponent*, who critically questions ("attacks") them in a regimented fashion. Every move in such an exchange corresponds to a structural element in the argumentation graph.

The first step in an analysis consists in segmenting the text into its argumentative discourse units (ADUs); these may in turn consist of several elementary discourse units (EDUs) as used in RST and SDRT (see below). The argumentation structure scheme then distinguishes between simple support (one ADU provides a justification of another) and linked support, where several ADUs collectively fulfil the role of justification. On the side of attacks, we separate rebutting (denying the validity of a statement) and undercutting (denying the relevance of a statement in supporting another). The scheme is designed in such a way that the fine-grained representations can be reduced to coarser ones that, for example, only distinguish between *support* and *attack* (see Peldszus and Stede (2015)), as it is customary in much of the related work on argumentation mining.

In Figure 2, we show the representation for the sample text given in Figure 1. The nodes of this graph represent the propositions expressed in text segments (grey boxes), and their shape indicates the role in the dialectical exchange: Round nodes are proponent's nodes, square ones are opponent's nodes. The arcs connecting the nodes represent different supporting (arrow-head links) and attacking moves (circle/square-head links). By means of recursive application of relations, representations of relatively complex texts can be created, identifying the central claim of a text, supporting premises, possible objections and their counter-objections.

These structures have been annotated on the German texts

github.com/peldszus/arg-microtexts. The finer segmented, multi-layer annotation done in this study for English is available at <https://github.com/peldszus/arg-microtexts-multilayer>.

by two experts, and they apply equally to the English translation. The guidelines are specified in Stede (2016). They have been shown to yield reliable agreement, see Peldszus (2014).

The annotated corpus contains 576 ADUs, of which 451 are proponent and 125 opponent ones. The most frequent relation is SUPPORT (263), followed by REBUT (108), UNDERCUT (63). LINKED relations (21) and support by EXAMPLE (9) occur only rarely.

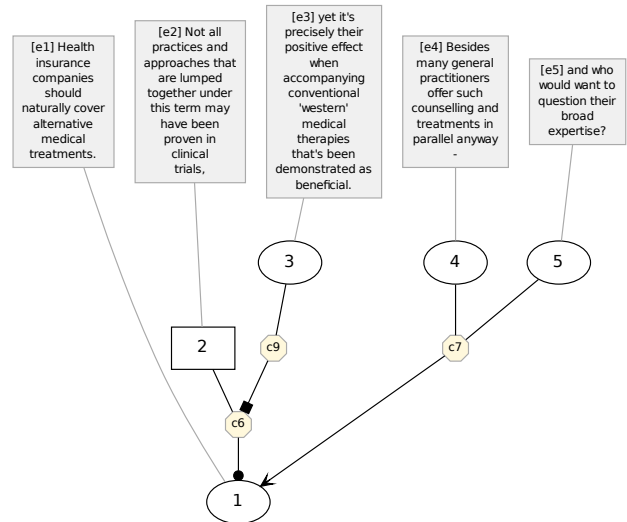


Figure 2: Argumentation structure of the example text

4. Discourse segmentation

In order to achieve comparable annotations on the three layers, we decided in the beginning of the project to aim at a common underlying discourse segmentation. For a start, the argumentation layer already featured ADU segmentation; these units are relatively coarse, so it was clear that any ADU boundary would also be an EDU boundary in RST and SDRT. On the other hand, the discourse theories often use smaller segments. Our approach was to harmonize EDU segmentation in RST and SDRT, and then to introduce additional boundaries on the argumentation layer where required, using an "argumentatively empty" JOIN relation.

As explained in the next two sections, RST and SDRT annotation start from slightly different assumptions regarding minimal units. After building the first versions of the structures (by the Toulouse and the Potsdam group, respectively), we discussed all cases of conflicting segmentations and changed both annotations so that eventually all EDUs were identical.

The critical cases fell into three groups:

- "Rhetorical" prepositional phrases: Prepositions such as 'due to' or 'despite' can introduce segments that are rhetorically (and sometimes argumentatively) relevant, when for instance a justification is formulated as a nominalized eventuality. We decided to overwrite the syntactic segmentation criteria with a pragmatic one and split such PPs off their host clause in cases where they have an argumentative impact.

- VP conjunction: These notoriously difficult cases have to be judged for expressing either two separate eventualities or a single one. We worked with the criterion that conjoined VPs are split in separate EDUs if only the subject NP is elided in the second VP.
- Embedded EDUs: For technical reasons, the Potsdam Commentary Corpus annotation had not marked center-embedded discourse segments; and, in general, different RST projects treat them in different ways. In SDRT, however, they are routinely marked as separate EDUs. In the interest of compatibility with other projects, we decided to build two versions of RST trees for texts with embedded EDUs: One version ignores them, while the other splits them off and uses an artificial “Same-Unit” relation to repair the structure (cf. Carlson et al. (2003)).

As a result of the finer segmentation, 83 ADUs not directly corresponding with an EDU have been split up, so that the final corpus contains 680 EDUs.

5. RST

The RST annotations have been created according to the guidelines (Stede, 2016) that were developed for the Potsdam Commentary Corpus (Stede and Neumann, 2014, in German). The relation set is quite close to the original proposal of Mann and Thompson (1988) and that of the RST website², but some relation definitions have been slightly modified to make the guidelines more amenable to argumentative text, as it is found in newspaper commentaries or in the short texts of the corpus we introduce here. Furthermore, the guidelines present the relation set in four different groups: primarily-semantic, primarily-pragmatic, textual, multinuclear. The assignment to ‘semantic’ and ‘pragmatic’ relations largely agrees with the subject-matter/presentational division made by Mann/Thompson and the RST website, but in some cases we made diverging decisions, again as a step to improve applicability to argumentative text; for example, we see EVALUATION as a pragmatic relation and not a semantic one. ‘Textual’ relations cover phenomena of text structuring; this group is motivated by the relation division proposed by Martin (1992), but the relations themselves are a subset of those of Mann/Thompson and the website (e.g., LIST, PREPARATION). Finally, the ‘multinuclear’ relations are taken from the original work, with only minor modifications to some definitions.

The annotation procedure explained in the guidelines suggests to prefer pragmatic relations over semantic ones in cases of ambiguity or doubt, which is also intended as a genre-specific measure. All RST annotations on the Microtext corpus were done by one of the authors of this paper using the RSTTool³. In the resulting corpus, there are 467 instances of RST relations, hence on average 4.13 per text. The most frequent relation is (by a large margin) REASON (178 instances), followed by CONCESSION (64), LIST

(63), CONJUNCTION (44), ANTITHESIS (32), ELABORATION (27), and CAUSE/RESULT (22); other relations occur less than 20 times.

Figure 3 shows the RST analysis of our sample text in Figure 1.

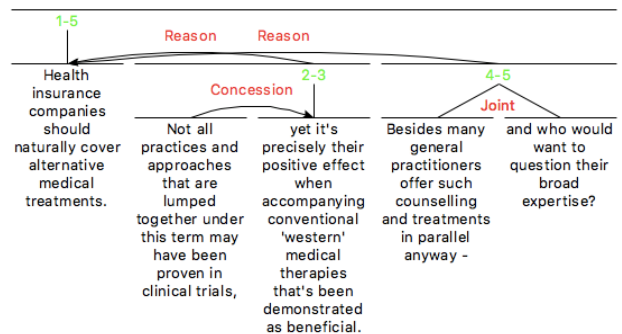


Figure 3: Rhetorical structure of the example text

6. SDRT

The SDRT annotations were created by one of this paper’s authors following the ANNODIS annotation manual (Muller et al., 2012a) which was based upon Asher and Lascarides (2003). The amount of information about discourse structure was intentionally restricted in this manual. Instead it focused essentially on two aspects of the discourse annotation process: segmentation and typology of relations. Concerning the first, annotators are provided with an intuitive introduction to discourse segments, including the fact that we allowed discourse segments to be embedded in one another as well as detailed instructions concerning simple phrases, conditional and correlative clauses, temporal, concessive or causal subordinate phrases, relative subordinate phrases, clefts, appositions, adverbials, coordinations, etc. Concerning discourse relations, the goal of the manual was to develop an intuition about the meaning of each relation. Occasional examples were provided, but we avoided an exhaustive listing of possible discourse markers that could trigger a particular relation, because many connectives are ambiguous and because the presence of a particular discourse connective is only one clue as to what the discourse relation linking two segments might be.⁴ For the purposes of this annotation campaign we used the Glozz annotation tool.⁵ The SDRT corpus contains 669 EDUs, 183 CDUs and 556 relations. The most frequent relations are CONTRAST (144), ELABORATION (106), CONTINUATION (80), RESULT (76), EXPLANATION (55), PARALLEL (26), CONDITIONAL (23) while the rest had fewer than 20 instances. Figure 4 shows the SDRT graph for the text shown in Figure 1.

⁴The manual also did not provide any details concerning the structural postulates of the underlying theory, including constraints on attachment (the so-called “right frontier” of discourse structure), crossed dependencies and more theoretical postulates. The goal of omitting such structural guidelines was the examination of whether annotators respected the right-frontier constraint or not (Afantenos and Asher, 2010).

⁵<http://www.glozz.org>

²www.sfu.ca/rst

³<http://www.wagsoft.com/RSTTool/>

One structural feature that distinguishes SDRT graphs from RST trees is the presence of complex discourse units or CDUs. Elementary Discourse Units (i.e. segments) are designated with numbers (1 through 5) while Complex Discourse Units are represented by π_1 and π_2 , dashed lines indicating member-hood in a CDU. Thus, we consider an SDRT discourse structure as a graph, (V, E_1, E_2, ℓ) , with a set V of discourse units; two types of edges, E_1 (relations) and E_2 (CDU membership), with $E_1, E_2 \subseteq V^2$; and ℓ a labelling function $\ell: E_1 \rightarrow \mathcal{T}$, where \mathcal{T} is a set of discourse relation types. CDUs are needed in SDRT in order to give an explicit representation of the exact scope of a discourse relation in the discourse structure. As shown in Figure 4, if an argument of a discourse relation involves several EDUs and perhaps even a small discourse structure, we need to group them together to form a single argument for the relation.

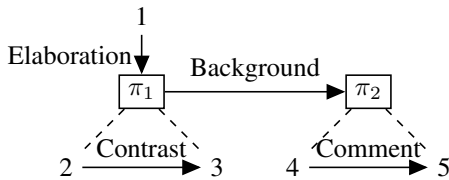


Figure 4: SDRT structure of the example text

7. Correlating the layers

7.1. Motivation for a common format

Calculating correlations between argumentation and discourse as well as between the two discourse corpora themselves requires converting the annotations from their tool-specific XML formats (RSTTool, Glozz) into a common format. This is not an easy task since the two theories have fundamental differences at least as far as scoping of relations is concerned. We consider dependency structures as a reasonable candidate for a common format capturing the structures of RST and SDRT, as it had also been proposed earlier by Danlos (2005). This is further facilitated by the fact that—with the exception of embedded EDUs in SDRT, for which we used the Same-Unit “relation” in RST—both annotations use the same EDUs.

In our case, dependency structures are graphs whose nodes represent the EDUs and whose arcs represent the discourse relations between the EDUs. Given this representation, calculating correlations between argumentation and discourse becomes an easy task since we have the same nodes, and only the relations vary.

Furthermore, future experiments on discourse parsing and argumentation structure analysis can be facilitated by using a common format for all annotations; however, we need to be cautious when it comes to theory-specific discourse parsing, since the mapping between the theories is not one to one, as we will see.

7.2. From Discourse Structures to Dependency Structures

As pointed out above, SDRT makes use of CDUs to represent larger units of discourse. RST, on the other hand,

makes use of some version of the “Nuclearity Principle” to determine what is the exact scope of a discourse relation. The presence of CDUs complicates our translation from SDRT graphs to a common dependency graph format capable of handling most RST trees and SDRT graphs (Perret et al., 2016). But most formulations of the Nuclearity Principle also hinder a structural match between RST trees and SDRT graphs, as detailed in Venant et al. (2013). The authors of this paper axiomatize both RST trees and SDRT graphs in an ecumenical fragment of monadic second order logic, so that precise translation results can be proved concerning the posited structures of the two theories. They show that if one restricts SDRT graphs to those that have just one incoming arc to each node, then one SDRT graph may correspond to several RST trees. On the other hand, the expressive capacities of SDRT outrun those of theories that require tree-like discourse structures, and Afantenos et al. (2015) have shown that we need this expressive capacity for multi-party dialogue. Nevertheless for the restricted and simplified texts that underlie the argumentation corpus, it seems that the two structures are largely inter-translatable, depending on (i) how we translate CDUs into a dependency graph and (ii) how we fix the arguments of relations in the translation of an RST tree into a dependency graph.

Another obvious mismatch concerns the labels of the relations in the two theories. Because RST and SDRT start from different explanatory goals, they employ different principles for individuating their sets of discourse relations. For example, our analyses of the sample text in Figures 3 and 4 show that an SDRT ELABORATION corresponds to REASON in the RST tree. Such differences can in principle be due to the different motivations of the theory (identify relations primarily on the basis of semantic properties of the argument, or on the grounds of interpreted speaker intentions), or they can result simply from different readings of the text by the respective analysts. Clarifying this in our corpus, and undertaking more principled comparisons between the theories is one goal for our future work with the aligned corpora.

Concerning the SDRT graphs, predicting full SDRSs (V, E_1, E_2, ℓ) with $E_2 \neq \emptyset$ has been to date impossible, because no reliable method has been identified in the literature for calculating edges in E_2 . Instead, most approaches (Muller et al., 2012b; Afantenos et al., 2015; Perret et al., 2016, for example) simplify the underlying structures by a *head replacement strategy* (HR) that removes nodes representing CDUs from the original hypergraphs and replacing any incoming or outgoing edges on these nodes on the *heads* of those CDUs, forming thus dependency structures and not hypergraphs. We adapted this strategy as well for the purposes of this paper. An example transformation is provided in Figure 5. The result of the transformation for the example text is shown in Figure 6b.

In the case of RST we follow the procedure that was initially proposed by Hirao et al. (2013) and later followed by Li et al. (2014). The first step in this approach includes binarizing the RST trees. In other words we transform all multi-nuclear relations into nested binary relations with the left-most EDU being the head. Dependencies go from nucleus to satellite. For illustration, a dependency structure

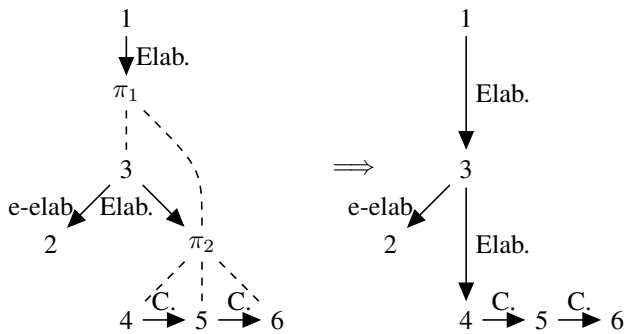


Figure 5: An example of SDRT dependency graph transformation

for the RST tree of Figure 3 is shown in Figure 6a.

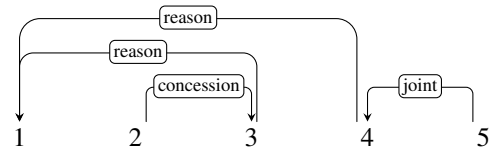
It is very important though to note that those transformations are not 1-1, meaning that although transforming RST or SDRT structures into dependency structures always produces the same structure, going back to the initial RST or SDRT structure is ambiguous.

For the argumentation structures, a dependency conversion based on ADUs had been presented by Peldszus and Stede (2015): Undercutting attacks, which target not ADUs but a relation between ADUs, can be converted to relations to the source of the attacked relation, given that all nodes have only one outgoing arc. For linked relations, which have more than one source, the left-most source node is taken as the head, while all further sources attach to the head with a LINK relation. Since the corpus presented here offers a more fine-grained segmentation into EDUs than the original segmentation into ADUs, we represent ADUs spanning over multiple EDUs by flat left-to-right JOIN relations, with the left-most EDU being the head with the original argumentative relation of the ADU. An example for the dependency conversion of the argumentation graph in Figure 2 is shown in Figure 6c.

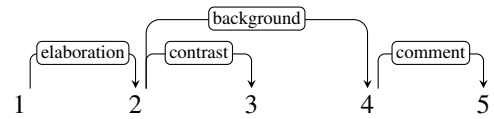
7.3. Correlations

Methodology The parallel annotation of the corpus converted to a dependency format now invites systematic comparison of the three structures. As we can see from in Figure 6, there are evident structural similarities between discourse structures—both RST and SDRT—and argumentative structure. Segment 1 holds the most prominent position in the SDRT graph, is the central nucleus in the RST tree, and the “main thesis” in the argumentation. The proponent/opponent distinction made in the argumentation analysis (circle vs. box node) of course has no direct counterpart in RST and SDRT, but the perspective switch between the two roles might be indicated by adversative coherence relations. For a quantitative, pair-wise comparison of the correspondences between related segments and the relation types, we apply two strategies: *common edges*, and *common connected components*.

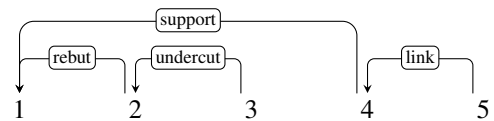
First, we look for undirected edges common to the different structures. In the example shown in Figure 6, an edge between 2 and 3 and between 4 and 5 is found in all structures. Note that the first ones all have an adversative rela-



(a) RST



(b) SDRT



(c) ARG

Figure 6: Example dependency conversions for the example text from the annotations of the three theories.

tion label, while the latter all have a more organizational relation label assigned. Argumentation and SDRT share an edge between 1 and 2, while argumentation and RST share an edge between 1 and 4. For the purpose of quantitative comparison, we collect the relations of all common edges in a cooccurrence matrix. Edges in one graph without a correspondence in the other graph are mapped to *none* in this matrix. An example matrix for argumentation and RST is shown in Table 1 and will be discussed below.

Furthermore, we extend the scope of analysis and look for connected components common to both structures. We apply a simple subgraph alignment algorithm yielding connected components with 2, 3 or 4 nodes occurring in the undirected, unlabelled graphs of both structures. This can reveal typical structural patterns. We can then determine how often these matches can be successfully mapped to one another given the relation labels. The structures shown in Figure 6 have for example several common components: All of them share a subgraph 1, 2, 3, although with different connection configurations. RST and argumentation additionally share a subgraph 1, 4, 5, with aligned connections. We will sum over the corpus, how often these common subgraphs occur and how likely they can be mapped to each other based on the relations.⁶

Argumentation vs. RST The cooccurrences of the edge-labels are shown in Table 1. In total, 60% of the edges are common in both structures. The most frequent class of SUPPORT edges in argumentation correspond mainly with REASON and some CAUSE and EVIDENCE edges, however 39% of them do not map to RST edges. The second frequent class in argumentation, REBUT, does not map well to RST: 72% of those edges have no correspondence in

⁶Note, that the comparisons in this subsection exclude 8 texts with center-embedding, as these complicate the correlation procedure here.

RST. The rest cooccurs with ANTITHESIS and CONCESSION. A very wide distribution of RST relation labels is found for the JOIN relation in argumentation. As mentioned in Section 7.2., this relations connects multiple EDUs to argumentatively relevant ADUs and is converted to dependencies in a left-to-right fashion. Since the nucleus in RST is not necessarily the left-most node, it correlates with both less argumentative relations such as CONJUNCTION or CONDITION and more argumentative relations such as REASON or CAUSE. For the argumentative UNDERCUTS, most of them align with CONCESSION and ANTITHESIS, while 33% do not cooccur with RST relations. Note, that nearly no correspondence can be found for RST LIST relations.

Regarding the common components in both theories, about 43% of all 3 node argumentation subgraphs can be matched to RST subgraphs, and 46% vice versa. Most of them are parallel structures, e.g. 2 SUPPORTS for a claim on the argumentation side and two parallel REASONS on the RST side. On the other hand there are also common subgraphs with differing edges, e.g. when the argumentation structure features two separate SUPPORTS or REBUTS, while the RST structure joins them into one larger span in a LIST or CONJUNCTION. Very interesting are the attack- and counter-attack constructions, some of which are shown in Figure 7. The RST annotations do not explicitly represent the rebutting functions of segments, but instead take the counter-attack as a reason for the claim. While the countering of an attack is implicitly supporting the attacked claim, supporting a claim cannot be taken as an implicit counter of potential attacks. The RST structure is thus missing one aspect of the attack- counter-attack structure.⁷ This also become evident by the different predictive power of this correspondence. For the linearisation with the claim first, the argumentation structure 7c can be mapped to the RST structure 7d in 81%, but vice versa only in 60%. For the linearisation with the claim behind, the situation is less clear: The argumentation structure 7a can be mapped to the RST structure 7b in 57%, vice versa in 67%. A more detailed comparison of the different subgraph correspondences is left for future work.

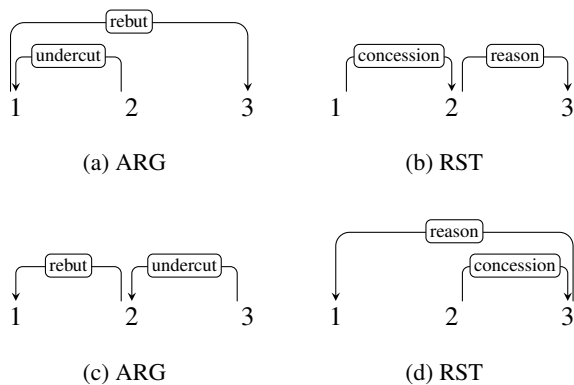


Figure 7: Common components between RST and ARG for attack-, counter-attack constructions.

⁷This point was already raised by Peldszus and Stede (2013), but could only now be investigated on a larger empirical basis.

	example	join	link	rebut	support	undercut	NONE
antithesis	.	3	.	9	1	6	7
background	.	1	2	.	4	.	8
cause	.	4	1	.	11	.	2
circumstance	.	4	1
concession	.	.	.	6	1	32	18
condition	.	13	.	1	1	.	.
conjunction	.	10	6	.	.	2	23
contrast	.	.	.	1	.	.	3
disjunction	.	2	2
e-elaboration	2	5	1
elaboration	4	7	.	2	3	.	11
evaluation-s	.	2
evidence	8	.	2
interpretation	2
joint	.	2	5	1	4	1	8
justify	4	.	3
list	.	1	.	1	2	.	53
means	.	1
motivation	.	.	.	1	2	.	.
preparation	.	3
purpose	.	3
reason	.	6	.	3	99	.	55
restatement	2	.	2
result	.	1	.	.	1	.	.
sameunit	.	1	.	1	.	.	.
solutionhood	1
unless	.	.	.	1	.	.	1
NONE	2	10	7	72	92	20	.

Table 1: Cooccurrence matrix for edge labels for RST (rows) vs Argumentation (columns).

Argumentation vs. SDRT When comparing common edges, we find that 63% of the edges can be mapped from one structure to the other. The cooccurrences of the relation labels are shown in Figure 2. Argumentative SUPPORTS cooccur with ELABORATION, EXPLANATION, and RESULT. However, 48% of the supports cannot be mapped to SDRT edges, which is more than in the alignment of argumentation and RST. REBUTS correspond mainly with CONTRAST, but also with ELABORATION, the remaining 43% of the rebutting edges do not map to SDRT, which is better than the coverage of RST for this relation. Undercutting attacks are quite clearly related to CONTRAST. As in RST, instances of the JOIN relations in argumentation structures distribute widely over the SDRT relations. From the SDRT perspective it is striking that nearly no correspondence is found for CONTINUATION relations. Also, 34% of the CONTRAST relations do not align with edges in the argumentation graphs.

Looking at the common components, we can not only investigate larger subgraphs but also consider the direction of the edges. Forward-looking supports (i.e. 1 supports 2) rather map to RESULT, while backward-looking supports (i.e. 2 supports 1) rather correspond with ELABORATIONS. EXPLANATIONS can be found for both directions of supports. In a similar vein, ELABORATIONS cooccur with REBUTS only, when the latter are backward-looking, not when

the rebutted claim comes after the rebuttal. CONTRASTS can be found for both directions of rebuttal.

For larger subgraphs with 3 nodes, 49% of the argumentation graphs can be mapped to SDRT, vice versa 53%. The most frequent correlation shown in Figures 8a and 8b. The common REBUT & UNDERCUT scheme in argumentation only maps to SDRT when linearized backward-looking. The SDRT correspondence of two CONTRASTS, as shown in Figures 8c and 8d, is only found in 35%, the remaining instances leave either the adversative character of the rebuttal or of the undercutter underspecified by using other relations such as ELABORATION, EXPLANATION or CONDITIONAL. As in RST, the identification of argumentative attacks and counter-attacks by chains of adversative relations is not trivially achieved and might require a deeper investigation of the surrounding signals.

	example	join	link	rebut	support	undercut	NONE
alternation	.	1	.	1	.	1	4
background	.	3	.	.	4	.	1
comment	1	2	2	.	2	.	2
conditional	.	12	.	3	.	1	1
continuation	1	2	1	.	5	1	62
contrast	.	6	1	35	6	39	45
e-elab	1	3
elaboration	4	8	3	10	46	.	26
explanation	.	4	1	2	33	.	6
frame	.	4	1	.	1	.	.
goal	.	.	1
narration	.	3	1	.	.	1	2
parallel	.	5	2	.	1	4	13
result	.	16	2	5	25	.	23
NONE	1	10	6	43	112	14	.

Table 2: Cooccurrence matrix for edge labels for SDRT (rows) vs Argumentation (columns)

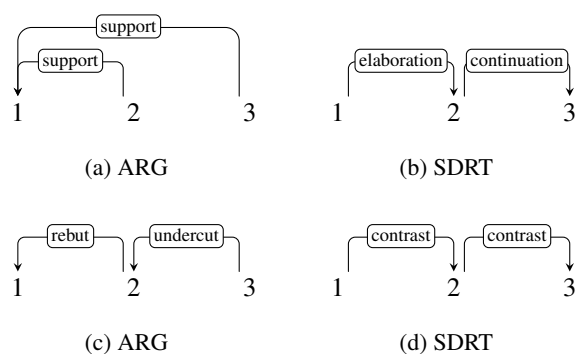


Figure 8: Common components between ARG and SDRT

8. Outlook

Our triply annotated corpus, with discourse annotations in the style of RST and SDRT and with an argumentation annotation, opens up several interesting lines of research that can now be pursued. Studying the connections between RST and SDRT, as well as between discourse and argumentation, is facilitated by the fact that we have transformed all

structures into a common dependency format. As far as discourse is concerned, Venant et al. (2013) have presented a formalism which allows the common representation of RST and SDRT structures and proves what correspondences are possible. For instance, they show that given the common formalism, every RST tree can be translated into an SDRS graph; on the other hand, SDRS graphs yield unique RST trees only under certain restrictions. For argumentation, however, so far it is an open problem to see exactly how argumentation graphs map onto to discourse structures and vice-versa. We believe this will be an important step to a better understanding on how various argumentation forms depend on discourse structure, and, more generally, how argumentation is linguistically realized.

The second task we plan to explore is finding new ways of learning models that can predict argumentation structures. Two alternatives can be identified. The first one is to directly predict argumentative structures without exploiting discourse structure, as has been previously performed for example by Peldszus and Stede (2015); we now plan to experiment with Integer Linear Programming (ILP) for this. The second approach is to investigate to what extent discourse structure is helpful for predicting argumentative structures; here, we will work on jointly learning a model both for discourse and argumentation. Finally we plan to investigate to what extend a common annotation of both RST and SDRT can help us jointly learn both discourse models.

9. Acknowledgements

This paper is supported by the ERC project STAC, Grant n. 269427, and by a grant in University Potsdam’s KROUP program.

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