Features for automatic discourse analysis of paragraphs

Daphne Theijssen, Hans van Halteren, Suzan Verberne and Lou Boves

Department of Linguistics, Redbud University Nijmegen

Abstract

In this paper, we investigate which information is useful for the detection of rhetorical (RST) relations between (Multi-) Sentential Discourse Units ((M-)SDUs)–text spans consisting of one or more sentences–within the same paragraph. In order to do so, we simplified the task of discourse parsing to a decision problem in which we decided whether an (M-)SDU is either rhetorically related to a preceding or a following (M-)SDU. Employing the RST Treebank (Carlson et al. 2003), we offered this choice to machine learning algorithms together with syntactic, lexical, referential, discourse and surface features. Next, the features were ranked on the basis of (1) models established by the classification algorithms and (2) feature selection metrics. Highly ranked features that predict the presence of a rhetorical relation are syntactic similarity, word overlap, word similarity, continuous punctuation and many reference features. Other features are used to introduce new topics or arguments: time references, proper nouns, definite articles and the word *further*.

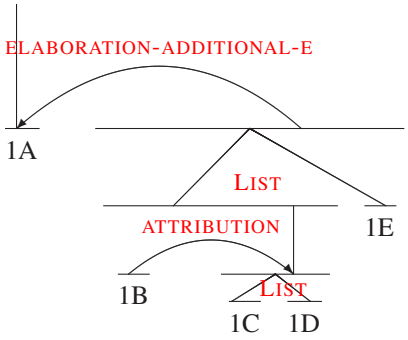
1 Introduction

In the field of language and speech technology, the analysis of discourse structures in texts receives much attention. A commonly used model for discourse analysis is Rhetorical Structure Theory (RST), which was developed by Mann and Thompson (1988). RST is based on the idea that rhetorical relations exist between adjacent spans of text, of which one span, called the NUCLEUS, is more important for the purpose of the author than the other spans, called the SATELLITES. Sometimes spans are equally vital; the relation is then named multi-nuclear. The smallest text spans that can hold rhetorical relations are named Elementary Discourse Units (EDUs). The popularity of RST has led to the development of an RST Treebank of manually annotated English texts, which is available for training and testing purposes (Carlson et al. 2003). It consists of 385 Wall Street Journal articles from the Penn Treebank (Marcus et al. 1993) with a total of 176,383 words. An example tree from the RST Treebank is presented in Figure 1.

The literature shows that various automatic RST parsers have been created. A state-of-the-art and publicly available system for automatic RST parsing of English texts is the one created by Soricut and Marcu (2003), which is Sentence-level PArsing of DiscoursE (SPADE). It produces an RST tree for every sentence in the input, but makes no attempt to find relations between sentences and at higher levels. Other researchers have also aimed at extracting rhetorical relations between text spans consisting of at least one sentence, which has resulted in the discourse parser RASTA (Rhetorical Structure Theory Analyzer), developed by Corston-Oliver (1998), and LeThanh's (2004) system DAS (Discourse Analyzing System). Both systems, however, are not generally available.

Apparently, a system for automatic discourse (RST) analysis that is suitable

Figure 1: Example RST tree



[Sun Microsystems Inc., a computer maker, announced the effectiveness of its registration statement for $125 million of 6 3/8% convertible subordinated debentures due Oct. 15, 1999.]^{1A} [The company said]^{1B} [the debentures are being issued at an issue price of $849 for each $1,000 principal amount]^{1C} [and are convertible at any time prior to maturity at a conversion price of $25 a share.]^{1D} [The debentures are available through Goldman, Sachs & Co.]^{1E} (wsj$_{0650}$)

for text analysis at all text levels is not available. SPADE provides a first step towards it by splitting sentences into EDUs and providing RST trees for each sentence. A second step could be to find relations between text spans consisting of at least one sentence within the same paragraph. The goal of this paper is to discover which information about the sentences may be useful for this second step. In other words, we attempt to answer the question: "Can we identify features that can be used to predict the presence of rhetorical (RST) relations between (Multi-)Sentential Discourse Units within paragraphs in English?" We introduce the term *(Multi-)Sentential Discourse Unit* ((M-)SDU) as a text span with a length of at least one sentence and at most one paragraph, forming a discourse unit in a text.[1]

In order to answer our research question, we reduced discourse analysis to a classification task that we offered to various machine learning algorithms together with an inventory of potentially relevant features. Next, we ranked the features with the help of the classification algorithms and feature ranking metrics.

The organization of this paper is as follows: In Section 2, we introduce the classification task, describe the potentially relevant features and present the accuracies reached by the classification algorithms. The ranking of the features is described in Section 3. The final Section (4) contains our overall conclusion and

[1] We should remark that (M-)SDUs that cover a full paragraph are not relevant here since they cannot be rhetorically related to another (M-)SDU in the same paragraph.

gives recommendations for future research.

2 Discourse analysis as a classification task

In order to determine which features may be relevant for automatic discourse analysis, we simplified the problem of RST discourse analysis to a task that can easily be performed by machine learning algorithms. Following Soricut & Marcu (2003), we limited ourselves to binary relations[2]. Also, we ignored the type and direction of the rhetorical relations to prevent data sparseness.

In a binary RST tree, we considered each *triple* of three adjacent (M-)SDUs $x - y - z$ in the same paragraph. Each (M-)SDU should be related to exactly one adjacent (M-)SDU, thus y is either related to x or to z. In other words, the RST relation holds between x and y (the left pair) or between y and z (the right pair). For example, 1BCD (y) in Figure 1 is rhetorically related to 1E (z), not to 1A (x). Each triple is a case in the machine learning task. The classification algorithms should classify the triples according to the position of the relation in the triple: on the *left* (x-y) or on the *right* (y-z).

With the help of a Perl script, we automatically extracted 2136 triples (1196 *right*, 940 *left*) from 942 different paragraphs in the RST Treebank.

2.1 Features

Machine learning algorithms need information about the triples to be able to classify them. We followed two strategies to establish an inventory of potentially relevant features: (1) by considering the literature on existing approaches taken by Corston-Oliver (1998), Marcu (1999), Marcu (2000) and LeThanh (2004), and (2) by studying a sample of the RST Corpus[3]. The result is a list of features that we subdivided into surface features, syntactic features, lexical features, reference features and discourse features.

Surface features

Marcu (1999) used the presence of words and part-of-speech (POS) tags as features in his machine learning approach. We included all lemmas and POS tags present in the data. For the purpose of lemmatization we employed the CELEX lexicon (Baayen et al. 1995), and we took the Part-of-Speech tags from the Penn Treebank. Our motivation to use lemmas rather than tokens or stems is that we believe that with lemmatization the word forms represent the full meaning of the original words while preventing word differences caused by the syntactic structure of the sentence. We also used trigrams containing either the word token or the POS tag in each slot. The (M-)SDU lengths (in sentences and in words) were taken into account as well.

[2] In the RST Treebank, 99% of the rhetorical relations are binary.

[3] The data sample consists of over 200 randomly selected relations from 30 randomly selected texts with a length of at least 5 sentences in the RST Treebank.

Since each lemma, POS tag and trigram was considered a separate feature, the number of surface features was too large (over 18,000) to be computationally feasible. We therefore chose the 1,000 most useful surface features according to the feature selection algorithm Relief (Kononenko 1994). Only these features have been applied in the experiments and analyses[4].

Syntactic features

In Corston-Oliver (1998), the syntactic features *tense* (e.g. past), *aspect* (e.g. progressive) and *polarity* (e.g. negative) are introduced. We have used similar information by counting the (relative) number of modals, infinitives, gerunds, past forms and present forms, and by checking the clauses for negation.

A potentially relevant feature we discovered in the sample of the RST Treebank is *syntactic similarity*, as exemplified in Table 1. The cue phrase *But* (see Lexical features) is also an important cue in this example.

Table 1: Example of syntactic similarity in wsj_0688

	SDU 1	SDU 2
adverb	-	*But*
PP	*For instance*	*on the West Coast, where profitable oil production is more likely than in the midcontinent region, the Bakersfield, Calif.*
NP subject	*employment in Denver*	*office staff of 130*
modal	*will*	*will*
lexical verb	*be reduced*	*grow*
PP	*to 105*	*by 175*
PP	*from 430*	*to 305*

Existing metrics to establish syntactic similarity were not suitable for our purpose: parser evaluation metrics such as *Parseval* (Black et al. 1991) require that the two compared structures describe the same sentence, and methods such as *document fingerprinting* (Bernstein and Zobel 2005) establish the similarity of larger texts, not of small units such as (M-)SDUs. We have developed a simple metric which determines the syntactic similarity of two (M-)SDUs by comparing their clause structures (Theijssen 2007).

Lexical features

The example illustrating syntactic similarity also indicated the relevance of cue phrases such as *but*, *for this reason*, *in short*, etc. This has also been argued by

[4]This selection was done separately for each individual training set in the ten-fold cross validation, as described in Section 2.2.

Corston-Oliver (1998), Marcu (1999), Marcu (2000) and LeThanh (2004). We have included all 207 cue phrases that LeThanh considers relevant above clause level[5]. LeThanh (2004) also introduced noun phrase (NP) and verb phrase (VP) cues such as *goal* (NP), *purpose* (NP and VP) and *result from* (VP). We included all her 41 NP and 56 VP cues in our experiments[6].

Other lexical features we found in the literature and the data sample were *word overlap* and *word similarity*. We defined three types of word overlap, namely the relative number of overlapping tokens, lemmas and stems. Word similarity was measured by employing Extended Gloss Overlap in *WordNet::Similarity* (Pedersen et al. 2004) and by consulting Lin's (1998) *Dependency Thesaurus*. In the example below, similar words are marked.

> *The FDA has said it **presented evidence** it uncovered to the company indicating that Bolar substituted the brand-name product for its own to gain government approval to sell generic versions of Macrodantin. Bolar has **denied** that it switched the brand-name product for its own in such testing.*
> — wsj_2382

Seeing data instances such as that below, we expected that the *presence of time references* could also be a relevant feature:

> *Until recently, Adobe had a lock on the market for image software, but last month Apple, Adobe's biggest customer, and Microsoft rebelled. Now the two firms are collaborating on an alternative to Adobe's approach, and analysts say they are likely to carry IBM, the biggest seller of personal computers, along with them.*
> — wsj_2365

Reference features

We found that many of the rhetorically related (M-)SDUs in the sample of the RST Treebank contained references. Referring to previously mentioned items by using personal pronouns, definite articles, demonstrative pronouns and (wh-)determiners (e.g. *which*) was therefore represented in features indicating their presence and their relative frequency in the (M-)SDU. We also established a list of 31 reference adverbs and adjectives (e.g. *other*) that we included in our approach. The list was based on the words found in the sample, supplemented with synonyms taken from the thesaurus of Microsoft Word 2003[7].

Corston-Oliver's (1998) system also includes an anaphora resolver which automatically finds the antecedents of reference words. Since the system is not generally available, we employed the anaphora resolution tool GuiTAR (Poesio and Alexandrov-Kabadjov 2004) to check whether an anaphoric relation was present between two (M-)SDUs.

[5] Only 21 of them were found in our total data set of 2136 triples.
[6] In our total data set of 2136 triples, 20 NP and 43 VP cues were present.
[7] The English thesaurus of Microsoft Word 2003 was developed for Microsoft by Bloomsbury Publ.

We here introduce a new feature *NP simplification*, being the lack of NP modifiers or NP heads in noun phrases that have been used previously in the text. Both types are illustrated below: the head *transaction(s)* in the first example, and the modifiers *Wall Street Journal's "American Way of Buying"* in the second example are missing in the second underlined phrase:

> *Grimm counted 16 transactions valued at $1 billion or more in the latest period, twice as many as a year earlier. The largest was the $12 billion merger creating Bristol-Myers Squibb Co.*
> — wsj_0645

> *When consumers have so many choices, brand loyalty is much harder to maintain. The Wall Street Journal's "American Way of Buying" survey found that 53% of today's car buyers tend to switch brands. For the survey, Peter D. Hart Research Associates and the Roper Organization each asked about 2,000 U.S. consumers about their buying habits.*
> — wsj_1377

Discourse features

This last type of features concerns information on the structure of the text. Frow what we saw in the sample of the RST Treebank, we expected that the presence of continuous punctuation is a helpful cue for the detection of rhetorical relations. In the example below, the second quotation part consists of more than one sentence, and moreover, both sentences are between (the same) brackets:

> *("A turban," she specifies, "though it wasn't the time for that 14 years ago. But I loved turbans.")*
> — wsj_1367

Also, we included information on the position of the (M-)SDU in the text (paragraph number) and in the paragraph (sentence number). The internal (binary) discourse structure of the (M-)SDU was also taken into account. We represented this by the number of EDUs and the nuclearity (NUCLEUS or SATELLITE) of both spans in the highest rhetorical relation. For example, if the internal discourse structure of an (M-)SDU is N1-S3, it contains a relation between a NUCLEUS span of 1 EDU and a SATELLITE span of 3 EDUs.

2.2 Method

We have formulated definitions for each of the features and have written Perl scripts for the automatic extraction of the feature values. Where possible, we used existing resources and tools, e.g. the syntactic analyses in the Penn Treebank. Depending on the form of the feature, its value had to be extracted for each (M-)SDU *x*, y and *z* in the triple, or for both pairs *x*-*y* and *y*-*z*. In total, 1,836 features were used, being the 1,000 best surface features, 20 syntactic features, 718 lexical features, 84 reference features and 14 discourse features. For details on the definition and extraction of the features, the reader is referred to Theijssen (2007).

We applied five machine learning algorithms: *Naive Bayes*, *k-Nearest Neighbours* (*kNN*), *Support Vector Machines* (*SVM*), *Decision Trees* and *Maximum Entropy*. The first four are present in the Orange software (Demsar et al. 2004) and we chose to employ those implementations. For Maximum Entropy we used the implementation of Zhang (2004). Since there was not enough data to establish the optimal parameters for each algorithm, we applied the algorithms with their default settings. The continuous features were made discrete by dividing their range into seven equal-frequency intervals with the 'discretization'-function in Orange, and were offered in this form to Naive Bayes and Maximum Entropy.

Due to the rather small number of triples, we decided to apply ten-fold cross-validation on all cases. It would not be fair to place some cases of a Wall Street Journal text in the train data and other cases of the same text in the test data. Therefore we had to manually split the data into partitions with equal numbers of triples and of texts. The 1,000 best surface features have been determined for each of the training sets. In total, 7,828 unique surface features have been selected.

2.3 Results

Since the machine learning task concerns choosing between only two classes (*left* and *right*), and the distribution of both classes is known, the machine learning results are represented by the *accuracy*, being the number of correctly classified cases in the test set divided by the total number of cases in the test set. The accuracies reached by the algorithms can be found in Table 2. They are compared with a baseline of selecting the most frequent class, which is *right* (56.0%).

Only Naive Bayes and Maximum Entropy reached an accuracy that is significantly better than the baseline. To check whether the other algorithms were affected by the large number of features and the low number of cases, we offered fewer features to them by employing Relief for feature selection, and selecting the best features for each partition. As expected, the performance of kNN, SVM and Decision Trees increased when fewer features were offered, but only SVM ever performed significantly better than the baseline [8].

Table 2: Accuracies reached

The significance (compared to the baseline) is indicated by the asterisks:
* $p<0.001$

baseline	Naive Bayes	kNN	SVM	DecTrees	MaxEnt
56.0%	60.0%*	51.1%	56.9%	53.1%	60.9%*

[8] When provided with the best 100 features: accuracy 58.7% with chi-square 6.17, $p<0.05$

2.4 Discussion

Despite our efforts to include good representations of all potentially relevant information, the accuracies reached by the machine learning algorithms were only slightly better than the baseline of 56.0%. An explanation for the results could be that the default settings in Orange were not optimal for the given task and data. The default k in kNN, for example, is the square root of the number of cases in the training set. We expect that a lower k could increase the accuracy reached and thereby the suitability of the system and its model. Adjusting the parameter setting is thus highly recommendable for future research.

Since it is not our goal to reach high accuracy on the classification task, but to establish what information (which features) are useful in the detection of rhetorical relations, the problem is less severe than it seems. Still, an important consequence of the low accuracies reached by these classification algorithms is that analyzing the models is speculative and should thus be performed with care.

3 Feature ranking

In order to discover which of the features in our feature set are most useful, we ranked them on the basis of four different metrics as described below.

3.1 Method

The four metrics can be subdivided in two groups: (1) metrics analysing the models of classification algorithms, and (2) feature ranking metrics.

The first two metrics are based on the models of Naive Bayes and Maximum Entropy described in the previous section. Given the significant improvement over the baseline, we believe Naive Bayes and Maximum Entropy were able to sift the information from the sets of features with some success. Assuming that this sifting is expressed in the model parameters, we attempted to extract an indication of feature importance. As for the systems that were not able to improve over the baseline, they were obviously unable to sift the information and any ranking is not likely to provide a useful measurement of feature importance.

To find a relevance score for the features following the model of Naive Bayes, we established the probability of each feature given the class. We approached this by considering both classes *left* and *right* and counting the number of times a certain feature value occurred with that class, and divided it by the total number of cases with the class in the training set. We then looped through all cases in the test set and divided the probability of the feature value given the correct class by the probability of the feature value given the incorrect class, and took the log. The result was the contribution of the feature value for that particular case. We then averaged the attributions over all cases in each fold to achieve a single relevance score for the feature.

Maximum Entropy considers each feature with each value separately and therefore established a weight (relevance score) for each feature-value combination. Since we need a relevance score per feature rather than per feature-value combina-

tion, we calculated a weighted average relevance score for each feature, using the frequencies of the feature values as weights. The result was averaged over the 10 training sets. The model also shows which class is best selected for which feature value, enabling us to establish the preferred class when a feature is *present* (binary features) or relatively high (continuous features). Sometimes, the preferred class of a continuous feature varied per frequency range and no general trend could be detected.

The second two metrics are the feature ranking metrics *Relief* (Kononenko 1994) and *Cluster Separation Score*, which has been developed by one of the authors (van Halteren).

Relief randomly selects a data instance and considers two types of nearest neighbours according to its feature values, namely one of the same class (the *nearest hit*) and one of a different class (the *nearest miss*). According to Relief, a feature with great predictive power is a feature that has equal (for discrete features) or similar (for continuous features) values in the same class, but different values in other classes. For the exact calculation, the reader is referred to Kononenko (1994). Orange includes an implementation of Relief with a default number of nearest neighbours (k) of 5[9].

The *Cluster Separation Score* (*CSS*) is determined for each feature by dividing the difference between the means of the values with class *left* and class *right* by the sum of the standard deviations of the values with class *left* and class *right*. The resulting relevance score is an indication of the extent to which the feature is able to distinguish the cases with class *left* from those with class *right*. As with the model of Maximum Entropy, the formula shows which class is best selected for which feature value. *CSS* requires that the feature values are continuous, which was problematic for our data since the great majority consists of discrete (nominal) features. We converted these features (such as the presence or absence of a POS tag) to numerical features with values *0* and *1*. We assumed that despite the fact that the features are not truly continuous, the metric will still be able to estimate the relevance of the features.

Since it is undesirable to draw conclusions on features that occur in only one partition of the data, we removed those from the four rankings found. They are features that only have the values *absent* and *not applicable* (for binary features) or *0* (for continuous features) in nine or ten partitions. From the total of 8,664 features[10], 806 features[11] remained after this removal.

The range and values of the relevance scores depend heavily on the definition of the metrics. Each of the metrics used the data to establish which features are more important than others in their own way, resulting in four different feature rankings that are not comparable. Therefore, we combined the ranking positions to reach a final ranked list. We assigned points to the features on the basis of their ranks in each of the four lists. The best feature received 1 point, the second 2, etc. Equally ranked features received equal ranking scores. We added up the ranking

[9] This default value, too, may in retrospect not be optimal for our investigation.
[10] 7,828 different surface, 20 syntactic, 718 lexical, 84 reference and 14 discourse features.
[11] 579 surface, 20 syntactic, 136 lexical, 61 reference and 10 discourse features.

scores in each of the four methods, leading to the final ranking.

3.2 Results

Since an overview of all 806 features would be too extensive to suit this paper and would include a discussion of irrelevant features at the bottom of the list, we limit ourselves to the 50 best features following our ranking. Note that the features have either been determined for all three (M-)SDUs *x*, *y* or *z*, or for both (M-)SDU pairs *x*-*y* and *y*-*z* in the triple. Therefore, the features have forms such as *the (x)*, being the presence of the word *the* in *x*, or *anaphora (y-z)*, being the presence of an anaphoric relation between *y* and *z*. This section presents the findings for each feature type. The top 10 can be found in Table 3.

Table 3: Top 10 of features

Rank	*Feature*	*Position*	*Feature type*
1	pers. pronoun in first clause	*z*	reference
2	def. article in first clause	*z*	reference
3	cont. quotation marks	*y*-*z*	discourse
4	past tense	*x*	syntactic
5	token overlap	*y*-*z*	lexical
6	personal pronoun	*z*	surface
7	time reference	*z*	lexical
8	missing modifier	*y*-*z*	reference
9	present tense	*x*	syntactic
10	lemma overlap	*y*-*z*	lexical

Surface features

Of the 579 surface features (words, POS tags and trigrams), 11 features are in our top 50. The trigrams are lacking in this list, probably because of the small size of our data set.

The following word features are included in the top 50: *a (y)*, *as (y)*, *farmer (z)*, *it (z)*, *little (y)*, *the (z)* and *to (y)*. The presence of the word *farmer* in this top 50 is probably caused by the specific text type and data set. The word *little* in *y* seems to refer back to *x*, because the relation is expected between *x* and *y* by the metrics of Maximum Entropy and CSS:

> *$_x$[If the pound falls closer to 2.80 marks, the Bank of England may raise Britain's base lending rate by one percentage point to 16%, says Mr. Rendell.]$_x$ −$_y$[But such an increase, he says, could be viewed by the market as "too little too late."]$_y$ $_z$[The Bank of England indicated its desire to leave its monetary policy unchanged Friday by declining*

> *to raise the official 15% discount-borrowing rate that it charges discount houses, analysts say.]$_z$*
> — wsj_0693

Pronouns are normally used to refer back to an earlier mentioned entity, and would thus signal a rhetorical relation with a previous (M-)SDU. When *it* occurs in *z*, the relation is indeed expected between *y* and *z*.

The relevance of the definite article *the* in *z* (ranked 15th) seems to confirm our intuition that *the* can be used as a reference word, and that references are important in discourse. However, in cases where *the* is present in *z*, CSS expects a relation between *x* and *y*, not between *y* and *z*, as in the example below:

> *$_x$[He made numerous trips to the U.S. in the early 1980s, but wasn't arrested until 1987 when he showed up as a guest of then-Vice President George Bush at a government function.]$_x$−$_y$[A federal judge in Manhattan threw out the indictment, finding that the seven-year delay violated the defendant's constitutional right to a speedy trial.]$_y$ $_z$[The appeals court, however, said the judge didn't adequately consider whether the delay would actually hurt the chances of a fair trial.]$_z$*
> — wsj_0617

Apparently, *the* is more often used to introduce a new topic or argument in the text. Journalists of the Wall Street Journal probably assume that readers are familiar with certain notions and topics (in this case *the appeals court*), thus mentioning them with the definite article.

POS tags that are in the top 50 are: *personal pronoun (y, z)*[12], *proper noun (z)* and *third person singular verb (x)*. Again we find that personal pronouns are cues that the (M-)SDU in which it appears is rhetorically related to the previous (M-)SDU. Proper nouns are common in financial newspaper texts. The metrics of Maximum Entropy and CSS show that when a proper noun is present in the *z*, the relation is most likely between *x* and *y*, and when in *y*, between *y* and *z*. Apparently, a person or company often introduces a new topic.

Syntactic features

The top 50 includes 8 of the 20 syntactic features. Both *present (x, z)* and *past (x)* tense are present in the top 50. Also included are *modals (z)*, *gerunds (y)* and *infinitives (x, y)*. Their relatively high ranking seems to indicate that syntactic structure is related to discourse structure.

Syntactic similarity was also in the top 50, but only for the left pair (*x*-*y*). CSS expects a rhetorical relation on the left when the syntactic similarity between *x* and *y* is high. This is what the literature and our data also suggested. For Maximum Entropy, the direction depends on the similarity range: the expected class varies per interval (in the discrete version of syntactic similarity), and no general trend could be found.

[12] The notation *personal pronoun (y, z)* represents two features: *personal pronoun (y)* and *personal pronoun (z)*.

Lexical features

Only 6 of the 718 lexical features belong to the 50 best features according to our method. Despite the fact that cue phrases are used in all systems discussed in the beginning of this paper, none of LeThanh's (2004) cue phrases and NP and VP cues come forward in our approach. A likely cause is the rather small size of the data set we employed.

Word overlap is ranked in the top 50 only for the right pair in the triple (*y*-*z*). A relatively high word overlap implies there is a rhetorical relation between the two (M-)SDUs concerned, which is what we expected.

The same expected pattern is found for *word similarity Lin (x-y, y-z)*. The higher the similarity, the higher the chance that a rhetorical relation exists. Word similarity on basis of WordNet is not present in the top 50. It is commonly known that the wide coverage of WordNet may lead to problems when applied to specific domains such as financial newspaper texts. Because Lin's Thesaurus was trained on Wall Street Journal texts, it is not surprising that the similarity based on Lin's Thesaurus is more useful for our task than that based on WordNet.

Time references are only useful enough to be in the top 50 when they occur in z. According to both CSS and the model of Maximum Entropy, the presence of a time reference in z indicates that the relation is probably between x and y. This would mean that time references introduce new topics that are not rhetorically related to the previous (M-)SDUs, for example as in:

> $_x$*[Witnesses have said the grand jury has asked numerous questions about Jacob F. "Jake" Horton, the senior vice president of Gulf Power who died in the plane crash in April.]*$_x-{}_y$*[Mr. Horton oversaw Gulf Power's governmental-affairs efforts.]*$_y$ $_z$*[On the morning of the crash, he had been put on notice that an audit committee was recommending his dismissal because of invoicing irregularities in a company audit.]*$_z$
> — wsj_0619

Note, however, that this example differs from the example in Section 2.1 where both *(M-)*SDUs in the relation contain a time reference. In order to also capture such instances, the co-occurrence of time references is best included as a separate feature in future research.

Reference features

Reference features are the most frequent (18) in the top 50[13]. The best two features according to our ranking method are also reference features: a *personal pronoun in the first clause (y-z)* and a *definite article in the first clause (y-z)*. As we already saw in the discussion of the surface feature *the* above, the presence of a definite article in the first clause of z indicates that the relation is between x and y. Apparently,

[13] In our feature set, reference features are always determined for (M-)SDU pairs. Since we expect reference items to refer back, features such as the presence of reference words or of a personal pronoun in the first clause always concern the second (M-)SDU of a pair.

definite articles are most often used to refer to what is assumed to be known, not to what has previously been mentioned in the article.

Still, most reference features in the top 50 confirm our intuitions that anaphoric references in different forms are cues for rhetorical relations. When there is an *anaphoric relation (x-y, y-z)* between two (M-)SDUs, it is an indication that there is a rhetorical relation. A high *relative number of demonstrative (z)* and *personal pronouns (y, z)*, and the *presence of personal pronouns (y, z)* also predict a rhetorical relation with the preceding (M-)SDU. The relevance of personal pronouns has already been found in the surface features, as discussed above.

Of the reference words in the top 50 (*added (z)*, *further (y)*, *less (y, z)*, *more (z)* and *other (y, z)*, only *further* shows a pattern that is unexpected. One would expect that the presence of *further* in *y* indicates that it refers back to *x* and thus that the relation is between *x* and *y*. This appears not to be the case. In our data, *further* seems to ask for an elaboration, for example:

> *$_x$[White House aides know it's a step that can't be taken lightly – and for that reason, the president may back down from launching a test case this year.]$_x$ $_y$[Some senior advisers argue that with further fights over a capital-gains tax cut and a budget-reduction bill looming, Mr. Bush already has enough pending confrontations with Congress.]$_y$–$_z$[They prefer to put off the line-item veto until at least next year.]$_z$*
> — wsj_0609

The last reference feature we defined, NP simplification, is present in the top 50 in the form of *missing modifiers (x-y, y-z)*. When there are missing modifiers, a relation is indeed expected in that (M-)SDU pair.

Discourse features

The top 50 includes 7 of the 14 discourse features available. Both features describing the position of the (M-)SDU in the text (the *paragraph number in the text (y, z)* and the *sentence number in the paragraph (x, y, z)*) are included. We believe the relevance of these features can be explained by the general structure of newspaper articles. This newspaper structure also makes itself felt in the feature *internal discourse structure (z)*. Testing these features on different text genres is necessary to establish whether our intuitions about newspaper structure are valid.

As expected, the presence of *continuous quotation marks (y-z)* is a cue for the presence of a rhetorical relation in both CSS and the model of Maximum Entropy.

3.3 Discussion

The list of best 50 features following our ranking strategy contains 'positive' features (expecting a rhetorical relation) as well as 'negative' features (introducing a new item in the text). Positive features are syntactic similarity, word overlap, word similarity (following Lin's (1998) Dependency Thesaurus), continuous punctuation and almost all reference features. Negative features include time references,

proper nouns, definite articles and the word *further*. Obviously, both positive and negative features are useful for discourse analysis.

Some features unexpectedly come forward from our approach as relevant. The word *farmer*, for example, is likely to be dependent on the data set and therefore a bad predictor. Similarly, the high ranking of discourse features such as the position of (M-)SDUs in the text and their internal discourse structure is probably caused by the general (financial) newspaper structure of the data. Results such as these can be prevented in future by extending the data with more texts of different genres. This may be difficult since no such data is available with discourse (i.e. RST) annotations yet.

4 Conclusion

In this paper, we have aimed at answering the question "Can we identify features that can be used to predict the presence of rhetorical (RST) relations between (Multi-)Sentential Discourse Units within paragraphs in English?" By reducing RST parsing to a classification problem, using an inventory of potentially relevant features (Section 2) and ranking them on the basis of the classification models and other metrics (Section 3), we have succeeded in this.[14] Some of the relevant features we have found predict the presence of a rhetorical relation (e.g. word similarity), while others are more often used to introduce new topics or arguments (the definite article for example).

In our research, we have limited ourselves to existing implementations of algorithms and metrics, without adjusting the parameters and without closely examining their capability to deal with our data. Also, we have reduced discourse analysis to a rather artificial classification task that is only a first step towards automatic discourse analysis. As this may have resulted in low accuracy and therefore only speculative rankings, we advise other researchers that plan to use our ranking to test the features on the real task with systems and settings that are more tuned to this kind of data.

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[14] The feature values, the Perl scripts and the feature relevance scores found can be downloaded from `http://lands.let.ru.nl/~daphne`.

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