Chapter

BuildingaDiscourse -TaggedCorpusinthe FrameworkofRhetoricalStructureTheory

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Abstract: Wedescribeourexperienceindevelopingadiscourse -annotatedcorpusforcommunity -wideuse.Workingin

theframeworkofRhetoricalStructureTheory,wewereabletocreatealargeannotatedresourcewithvery highconsistency,usingawell -definedm ethodologyandprotocol.Thisresourceismadepubliclyavailable throughtheLinguisticDataConsortiumtoenableresearcherstodevelopempiricallygrounded,discourse -

specificapplications.

Keywords: discourse, corpus, annotation, rhetorical structure

1. INTRODUCTION

Theadventoflarge -scalecollectionsofannotateddatahasmarkedaparadigmshiftintheresearch communityfornaturallanguageprocessing. Thesecorpora, nowalsocommoninmanylanguages, haveaccelerateddevelopmenteffortsandenergize dthecommunity. Annotationrangesfrombroad characterizationofdocument -levelinformation, suchastopicorrelevancejudgments (Voorheesand Harman, 1999; Wayne, 2000) to discreteanalysis of awiderange of linguistic phenomena. However, rich theoretical approaches to discourse/textanalysis (Van Dijkand Kintsch, 1983; Meyer, 1985; Groszand Sidner, 1986; Mannand Thompson, 1988) haveyet to be applied on a large scale. So far, the annotation of discourse structure of documents has been applied primar ilytoidentifying to pical segments (Hearst, 1997), inter -sentential relations (Nomoto and Matsumoto, 1999; Ts'ou et al. 2000), and hierarchical analyses of small corpora (Moserand Moore, 1995; Marcu et al. 1999).

Inthispaper, were count our experience indevelopingalargeresourcewithdiscourse -level annotation for NLP research. Our main goal in under taking this effort was to create a reference corpus forcommunity -wideuse. Two essential considerations from the outsetwere that the corpus needed to beconsistently annotated, and that it would be made publicly available through the Linguistic Data Consortium for a nominal feet occover distribution costs. The paper describes the challenges we faced inbuildingacorpusofthislevelofcomplexityandsc ope -includingselectionoftheoretical approach, annotation methodology, training, and quality assurance. The resulting corpus contains 385 documents of American English selected from the Penn Treebank (Marcus etal. 1993), hierarchically annotated in the framework of Rhetorical Structure Theory (Mannand Thompson, 1988). In the paper, wealsoshowhowthecorpuscanbeminedinordertostudyavarietyoflinguisticphenomenathat rangefromtheroleofcuephrasesinsignalingdiscourserelationstoiss uespertainingtohigh -level writingstrategies.Ourpreliminaryanalysisillustratesthepotentialofthiscorpusasarichnewsource ofmulti -layereddiscourseinformationtosupportmultiplelinesofresearchforlanguage understandingapplications.

2. FRAMEWORK

Twoprinciplegoalsunderpinthecreationofthisdiscourse -taggedcorpus:1)Thecorpusshouldbe groundedinaparticulartheoreticalapproach,and2)itshouldbesufficientlylargetoofferpotential forwide -scaleuse -includinglinguistica nalysis,trainingofstatisticalmodelsofdiscourse,andother computationallinguisticapplications. Thesegoalsnecessitatedanumberofconstraintstoour approach. Wefocusedonannotatingalargecorpusoftextualmaterial,anddidnotaddressthe applicabilityofourapproachtospokenlanguagecorpora. Thetheoreticalframeworkhadtobe practicalandrepeatableoveralargesetofdocumentsinareasonableamountoftime, witha significantlevelofconsistencyacrossannotators. Thus, ourapproach contributestothecommunity quitedifferentlyfromdetailedanalysesofspecificdiscoursephenomenaindepth, suchasanaphoric relations(Garside *etal.* 1997)orstyletypes(Leech *etal.* 1997);analysisofasingletextfrommultiple perspectives(Man nandThompson,1992);orillustrationsofatheoreticalmodelonasingle representativetext(BrittonandBlack,1985;VanDijkandKintsch,1983).

OurannotationworkisgroundedintheRhetoricalStructureTheory(RST)framework(Mannand Thompson,198 8). WedecidedtouseRSTforthreereasons:

- Itisaframeworkthatyieldsrichannotationsthatuniformlycaptureintentional,semantic,and textualfeaturesthatarespecifictoagiventext.
- Previousresearchonannotatingtextswithrhetoricalstructur etrees(Marcu etal. 1999)hasshown thattextscanbeannotatedbymultiplejudgesatrelativelyhighlevelsofagreement. Weaimedto produceannotationprotocolsthatwouldyieldevenhigheragreementfigures.
- PreviousresearchhasshownthatRSTtrees canplayacrucialroleinbuildingnaturallanguage generationsystems(Hovy,1993;MooreandParis,1993;Moore,1995)andtextsummarization systems(Marcu,2000);canbeusedtoincreasethenaturalnessofmachinetranslationoutputs (Marcu etal .200 0);andcanbeusedtobuildessay -scoringsystemsthatprovidestudentswith discourse-basedfeedback(Burstein etal .2001).WesuspectthatRSTtreescanbeexploited successfullyinthecontextofotherapplicationsaswell.

IntheRSTframework,thed iscoursestructureofatextcanberepresentedasatreedefinedin termsoffouraspects:

- Theleaves of the tree correspond to text fragments that represent the minimal units of the discourse, called *elementary discourse units*
- Theinternalnodesofthe treecorrespondtocontiguoustext spans
- Eachnodeischaracterizedbyits *nuclearity* –anucleusindicatesamoreessentialunitof information, whileasatelliteindicatesasupportingorbackgroundunitofinformation.
- Eachnodeischaracterizedbya *rhetoricalrelation* thatholdsbetweentwoormorenon overlapping,adjacenttextspans.Relationscanbeintentional,semantic,ortextualinnature.

Below, we describe the protocol that we used to build consistent RST annotations.

2.1 Segmenting Texts into Units

Thefirststepincharacterizingthediscoursestructureofatextinourprotocolistodeterminethe elementarydiscourseunits(EDUs),whicharetheminimalbuildingblocksofadiscoursetree.Mann andThompson(1988,p.244)statethat"RSTprov idesageneralwaytodescribetherelationsamong clausesinatext,whetherornottheyaregrammaticallyorlexicallysignalled."Yet,applyingthis intuitivenotiontothetaskofproducingalarge,consistentlyannotatedcorpusisextremelydifficult, becausetheboundarybetweendiscourseandsyntaxcanbeveryblurry.Theexamplesbelow,which

rangefromtwodistinctsentencestoasingleclause, all conveyessentially the same meaning, packaged in different ways:

- 1. [XeroxCorp.'sthird -quarternetinc omegrew6.2%on7.3%higherrevenue.][Thisearnedmixed reviewsfromWallStreetanalysts.]
- 2. [XeroxCorp'sthird -quarternetincomegrew6.2%on7.3%higherrevenue,][whichearnedmixed reviewsfromWallStreetanalysts.]
- 3. [XeroxCorp'sthird -quarternet incomegrew6.2%on7.3%higherrevenue,][earningmixed reviewsfromWallStreetanalysts.]
- 4. [The 6.2% growth of Xerox Corp.'s third reviews from Wall Street analysts.] -quarternetin come on 7.3% higher revenue earned mixed

In Example 1, there is a consequent and in the relation between the first and second sentences. Ideally, we would like to capture that kind of the torical information regardless of the syntactic form in which it is conveyed. However, a sexamples 2 -4 illustrate, separating rhetorical from syntactical values is some captures and the syntactical values of the syntactic can always is some conveyed. It is in evitable that any decision on how to bracket elementary discourse units necessarily involves some compromises.

Reseachersinthefieldhaveproposedanumberofcompetinghypothesesaboutwhatconstitutesan elementarydiscourseunit. Whilesometaketheelementaryunitstobeclauses (Grimes, 1975; Givon, 1983; Longacre, 1983), otherstakethemtobeprosodicunits (Hirschbergand Litman, 1993), turnsof talk (Sacks, 1974), sentences (Polanyi, 1988), intentionally defined discourses egments (Groszand Sidner, 1986), orthe "contextually indexed representation of information conveyed by a semiotic gesture, asserting a single state of affairs or partial state of affairs in a discourse world," (Polanyi, 1996, p. 5). Regard less of their theoretical stance, all agree that the elementary discourse units are non overlapping spans of text.

Ourgoalwastofindabalancebetweengranularityoftaggingandabilitytoidentifyunits consistentlyonalargescale.Intheend,wecho setheclauseastheelementaryunitofdiscourse,using lexicalandsyntacticcluestohelpdetermineboundaries:

- 5. [Although Mr. Freemanisretiring,] [hewill continue towork as a consultant for American Expresson a project basis.] w_{sj_1317}
- 6. [BondCorp., abrewing,property,mediaandresourcescompany,issellingmanyofitsassets][**reduce**itsdebts.] wsi 0630

to

 $However, clauses that are subjects, objects, or complements of a main verbare not treated as \ EDUs; \\$

- 7. [Makingcomputerssmaller oftenmeans sacrificingmemory .] wsj 2387
- 8. [The company's current management found itself $\mathbf{lockedintothis}$, "he said.] \mathbf{wsj}_{1103}

Relative clauses, nominal post modifiers, or clauses that break upother legitimate EDUs, are treated a sembed ded discourse units:

- 9. [The results under score Sears's difficulties] [inimplementing the "every day low pricing" strategy...] $_{\rm wsj_1105}$
- 10. [TheBushAdministration,] ¹[tryingtobluntgrowingdemandsfromWesternEuropefora relaxationofcontrolsonexportstotheSovietbloc ,][isquestioning...] _{wsj_2326}

¹Inthisexample, *TheBu shAdministrationisquestioning* isactuallyasingleEDU,interruptedbytheembeddeddiscourse unit, *tryingtoblunt*... Usingtheannotationtool,the SAME-UNITrelationisselectedtogroupthetwopartsoftheunitback together.

Finally, asmallnumber of phrasal EDUs are allowed, provided that the phrase begins with a strong discoursemarker, such as because, inspite of, as a result of, according to . We opted for consistency in segmenting, sacrificing some potentially discour se-relevant phrases in the process.

2.2 BuildinguptheDiscourseStructure

Oncetheelementaryunitsofdiscoursehavebeendetermined, adjacentspansarelinkedtogether viarhetoricalrelations, creating a hierarchical structure. Relations may be mononucle aror multinuclear. Mononuclear relations hold between two spans and reflect the situation in which one span,the *nucleus*,ismoresalienttothediscoursestructure,whiletheotherspan,the satellite, representssupportinginformation.Multinuclearrela tionsholdamongtwoormorespans, each of which has equal weight in the discourse structure. A total of 53 mononuclear and 25 multinuclear relationswereusedforthetaggingoftheRSTCorpus.Thefinalinventoryofrhetoricalrelationsis datadriven, andisbasedonextensiveanalysisofthecorpus. Although this inventory is highly detailed, annotators strongly preferred keeping a higher level of granularity in the selections available tothemduringthetaggingprocess. More extensive analysis of the finaltaggedcorpuswill demonstratetheextenttowhichindividualrelationsthataresimilarinsemanticcontentwere distinguishedconsistentlyduringthetaggingprocess. Althoughour corpus contained a number of differentgenres(e.g.,editorials,le ttersandinformativearticles), applicability of this relation setto a broaderrangeofgenresmaygiverisetotheneedforadditionrhetoricalrelations.

The 78 relations used in annotating the corpuscan bepartitioned into 16 classes that share some type of rhetorical meaning 2:

- Attribution:attribution,attribution -negative
- Background: background, circumstance
- *Cause:*cause,result,consequence
- *Comparison*:comparison,preference,analogy,proportion
- Condition: condition, hypothetical, contingency, o therwise
- Contrast:contrast,concession,antithesis
- *Elaboration*:elaboration -additional,elaboration -general-specific,elaboration -part-whole, elaboration-process-step,elaboration -object-attribute,elaboration -set-member,example, definition
- Enablement:p urpose,enablement
- Evaluation: evaluation, interpretation, conclusion, comment
- Explanation: evidence, explanation argumentative, reason
- *Joint:* list, disjunction
- Manner-Means: manner, means
- *Topic-Comment:* problem -solution, question -answer, statement -response, topic -comment, comment-topic, rhetorical -question
- Summary:summary,restatement
- Temporal:temporal -before,temporal -after,temporal -same-time,sequence,inverted -sequence
- TopicChange: topic -shift,topic -drift

Inaddition,threerelationsareusedtoi mposestructureonthetree:textual -organization,span,and same-unit(usedtolinkpartsofunitsseparatedbyanembeddedunit orspan).

²Manyrelationsinclude variantsbasedonnuclearityassignment,whicharenotincludedhere.Thecompletelistofrelations canbeviewedinthetaggingguidelines(CarlsonandMarcu,2001).

3. DISCOURSEANNOTATIONTASK

OurmethodologyforannotatingtheRSTCorpusbuildsonpriorcorpusworkintheRhetorica StructureTheoryframeworkbyMarcu *etal.* (1999).Becausethegoalofthiseffortwastobuilda high-quality,consistentlyannotatedreferencecorpus,thetaskrequiredthatweemploypeopleas annotatorswhoseprimaryprofessionalexperiencewasinth eareaoflanguageanalysisandreporting, provideextensiveannotatortraining,andspecifyarigoroussetofannotationguidelines.

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3.1 AnnotatorProfileandTraining

Theannotatorshiredtobuildthecorpuswereallprofessionallanguageanalystswithprior experienceinothertypesofdataannotation. Theyunderwentextensivehands -ontraining, which took placeroughly in three phases. During the orientation phase, the annotators were introduced to the principles of Rhetorical Structure Theory and the disco urse-tagging tool used for the project (Marcuet al., 1999). The toolenables an annotator to segment at extintounits, and then build upahier archical structure of the discourse. In this stage of the training, the focus was on segmenting hard copytext into EDUs, and learning the mechanics of the tool.

Inthesecondphase, annotators beganto explore interpretations of discourse structure, by independently tagging as hort document, based on an initial set of tagging guidelines, and then meeting as a roup to compare results. The initial focus was on resolving segmentation differences, but over time this shifted to addressing is sues of relations and nuclearity. These exploratory sessions led to enhancements in the tagging guidelines. To reinforce new u les, annotators reaged the document. During this process, we regularly tracked inter - annotator agreement (see Section 4.2). In the final phase, the annotation team concentrated on way stored uced if ferences by adopting some heuristics for hand ling higher revels of the discourse structure.

Wiebe etal. (1999)presentsamethodologyforimprovinginter -coderreliabilityusing automaticallygenerated,bias -correctedtags.ItislikelythatWiebe'smethodcouldbeusedtoimprove tations as well. However, applying this method in our context would have thereliabilityofouranno etal. (1999)consistedin beenbynomeansatrivialprocess. The annotation task considered by Wiebe labellingas" objective "or "subjective" asample of independently generated sen tences.Incontrast,in ourtask, the examples were not independent. Decisions made by an annotator at a given step affected thedecisionsmadeatsubsequentstepsoftheannotation .Ourmethodologyfordeterminingthe"best" guidelineswasmuchmoreofa consensus-buildingprocess, taking into consideration multiple factors ateachstep. The final tagging manual, about 80 pages in length, contains extensive examples from the corpustoillustratetextsegmentation, nuclearity, selection of relations, and di manualcanbedownloadedfromthefollowingwebsite: http://www.isi.edu/~marcu/discourse.

Theactualtagging of the corpus progressed in three developmental phases. During the initial phase of about four months, the team created a preliminary corpus of 100 tagged documents. This was followed by a month reassessment phase, during which we measured consistency a cross the group on a select set of documents, and refined the annotation rules. At this point, we decided to proceed by pre-segmenting all of the texts on hard copy, to ensure a higher over all quality to the final corpus. Each text was presented by two annotators; discrepancies were resolved by the author of the tagging guidelines. In the final phase (about six months) all 100 documents were reagged with the new approach and guidelines. The remainder of the corpus was tagged in this manner.

3.2 TaggingStrategies

Annotatorsdevelopeddifferentstrategiesforanalyzingadocumentandbuildingupthe correspondingdiscoursetree. Thereweretwobasicorientationsfordocumentanalysis –hardcopyor graphicalvisualizationwiththetool.Hardcopyanalysisrangedfromjottingofnotesinthemarginsto markingupthedocumentintodiscoursesegments.Thosewhopreferredagraphical orientation

performed their analysis simultaneously with building the discourse structure, and we remore likely to build the discourse tree inchunks, rather than incrementally.

Weobservedavarietyofannotationstylesfortheactualbuildingofadisco ursetree.Twoofthe morerepresentativestylesareillustratedbelow.

- 1. Theannotatorsegmentsthetextoneunitatatime,thenincrementallybuildsupthediscoursetree byimmediatelyattachingthecurrentnodetoapreviousnode. Whenbuildingthetree inthis fashion,theannotatormustanticipatetheupcomingdiscoursestructure,possiblyforalargespan. Yet,oftenanappropriatechoiceofrelationforanunseensegmentmaynotbeobviousfromthe current(rightmost)unitthatneedstobeattached. Thatiswhyannotatorstypicallyusedthis approachonshortdocuments,butresortedtootherstrategiesforlongerdocuments.
- 2. Theannotatorsegmentsmultipleunitsatatime,thenbuildsdiscoursesub -treesforeachsentence. Adjacentsentencesarethenl inked,andlargersub -treesbegintoemerge.Thefinaltreeis producedbylinkingmajorchunksofthediscoursestructure. Thisstrategyallowstheannotatorto seetheemergingdiscoursestructuremoreglobally;thus,itwasthepreferredapproachforlo nger documents.

Considerthetextfragmentbelow, consisting of foursentences, and 11 EDUs:

[Still,analystsdon'texpectthebuy -backtosignificantlyaffectper -shareearningsintheshort term.] 16 ["Theimpactwon'tbethatgreat,"] 17 [saidGraemeLid gerwoodofFirstBostonCorp.] 18 [This isinpartbecauseoftheeffect] 19 [ofhavingtoaveragethenumberofsharesoutstanding,] 20 [she said.] 21 [Inaddition,] 22 [Mrs.Lidgerwoodsaid,] 23 [Norfolkislikelytodrawdownitscashinitially] [tofinance thepurchases] 25 [andthusforfeitsomeinterestincome.] 26 $_{\text{wsj_1111}}$

The discourses ub -tree for this text fragment is given in Figure 1. Using Style 1 the annotator, upon segmenting unit [17], must anticipate the upcoming *example* relation, which spans un its [17 -26]. However, even if the annotator selects an incorrect relation at that point, the tool allows great flexibility in changing the structure of the tree later on.

UsingStyle2,theannotatorsegmentseachsentence,andbuildsupcorrespondingsub -treesfor spans[16],[17 -18],[19 -21]and[22 -26].Thesecondandthirdsub -treesarethenlinkedviaan *explanation-argumentative* relation,afterwhich,thefourthsub -treeislinkedviaan *elaboration-additional*relation.Theresultingspan[17 -26]isf inallyattachedtonode[16]asan *example*satellite.

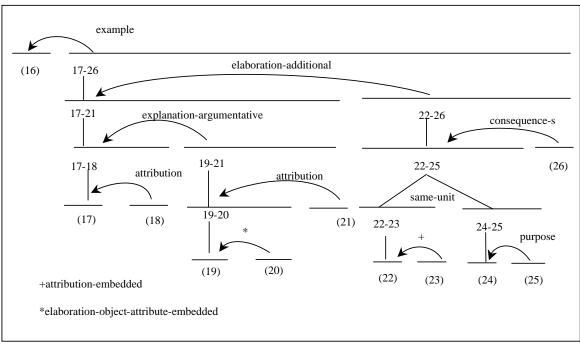


Figure 1.Discoursesub -treeformultiplesentences

4. QUALITYASSURANCE

Anumberofstepsweretakentoensurethequalityofthefinaldiscoursecorpus. These involved twotypesoftasks: checkingthevalidityofthetreesandtrackinginter -annotatorconsistency.

4.1 TreeValidationProcedures

Annotatorsreviewedeachtreeforsyntacticandsemanticvalidity. Syntacticchecking involved ensuring that the tree hada single root node and comparing the tree to the document to check for missing sentences or fragments from the end of the text. Semantic checking involved reviewing nuclearity assignments, as well as choice of relation and level of attachment in the tree. A lltrees were checked with a discourse parser and tree travers alprogram which of tenidentified errors undetected by the manual validation process. In the end, all of the trees worked successfully with the seprograms.

4.2 MeasuringConsistency

Wetrackedinter -annotatoragreementduringeachphaseoftheproject,usingamethoddeveloped byMarcu *etal.* (1999)forcomputingkappastatisticsoverhierarchicalstructures. Thekappa coefficient(SiegelandCastellan,1988) hasbeenusedextensivelyinpreviousemp iricalstudiesof discourse(Carletta *etal.* 1997;FlammiaandZue,1995;PassonneauandLitman,1997). Itmeasures pairwiseagreementamongasetofcoderswhomakecategoryjudgments, correctingforchance expectedagreement. ThemethoddescribedinMarc u *etal.* (1999)mapshierarchicalstructuresinto setsofunitsthatarelabeledwithcategorialjudgments. Thestrengthsandshortcomingsofthe approacharealsodiscussedindetailthere. Researchersincontentanalysis(Krippendorff, 1980)

suggestthat valuesofkappa>0.8reflectveryhighagreement,whilevaluesbetween0.6and0.8 reflectgoodagreement.

Table 1 shows average kappa statistics reflecting the agreement of three annotators at various stages of the tasks on selected documents. Differen tsets of documents were chosen for each stage, with no overlap indocuments. The statistics measure annotation reliability at four levels: elementary discourse units, hierarchical spans, hierarchical nuclearity and hierarchical relation assignments.

Ther esultsofTable1showsignificantimprovementovertimeatalllevelsofannotation.Atthe unitlevel, the initial (April 00) scores and final (January 01) scores representagreement on blind segmentation, and are shown in bold face. The interim June and Novemberscoresrepresentagreement -segmentedtexts.Inthesecases,twoannotatorsindependentlysegmenteda basedonhardcopypre hardcopyofeachdocumentintoEDUs.Discrepancieswereresolvedbytheannotationteamleader, anda"goldstandard"anno tatedhardcopywasproduced. This version was given to the annotator (or -tagged documents) responsible for building the discourse tree for thatannotators, for double document. Notice that even for the sepre -segmenteddocuments,agreementattheunitleve lisnot 100% perfect, ranging from .95to 1.00, because of human errors that were introduced when transferringthesegmentationfromhardcopyintotheannotationtool. Atypical example of such an errorwouldbeinsertingaunitboundarybeforeanend -of-sentencequotationmarkorperiod.AsTable 1shows, alllevels demonstrate a marked improvement from Aprilto November (when thefinal corpuswascompleted), ranging from about 0.77 to 0.92 at the spanlevel, from 0.70 to 0.88 at the nuclearitylevel, an dfrom 0.60 to 0.79 at the relation level. In particular, when relations are combined into the 16 rhetorically related classes discussed in Section 2.2, the November results of the annotation processareextremelygood. The Fewer -RelationsColumnshowsthe improvementinscoreson assigning relations when they are grouped in this manner, with November results ranging from 0.78 to 0.82 overthethree pairs of annotators. In order to see how much of the improvement had to do with pre-segmenting, weasked the samethreeannotatorstoannotatefivepreviouslyunseendocumentsin January, without reference to a pre -segmenteddocument. The results of this experimentare given in the last row of Table 1, and the yreflect only a small over all decline in performancefromthe Novemberresults. Thesescores reflective rystrong agreement and represent a significant improvement overpreviously reported results on annotating multiple texts in the RST framework (Marcula and Marcula and Marcuetal. 1999).

Table 1. Inter -annotatoragreement --periodicresultsforthreetaggers

| Taggers | Units | Spans | Nuclearity | Relations | Fewer- Relations | No.ofDocs | Avg.No. EDUs |
|-----------------------|----------|----------|------------|-----------|---------------------|-----------|-----------------|
| A,B,E | 0.874407 | 0.772147 | 0.705330 | 0.601673 | 0.644851 | 4 | 128.750000 |
| (Apr00) | | | | | | | |
| A,B,E | 0.952721 | 0.844141 | 0.782589 | 0.708932 | 0.739616 | 5 | 38.400002 |
| (Jun00) | | | | | | | |
| A,E | 0.984471 | 0.904707 | 0.835040 | 0.755486 | 0.784435 | 6 | 57.666668 |
| (Nov00) | | | | | | | |
| B,E | 0.960384 | 0.890481 | 0.848976 | 0.782327 | 0.806389 | 7 | 88.285713 |
| (Nov00) | | | | | | | |
| A,B | 1.000000 | 0.929157 | 0.882437 | 0.792134 | 0.822910 | 5 | 58.200001 |
| (Nov00) | | | | | | | |
| A,B , E | 0.971613 | 0.899971 | 0.855867 | 0.755539 | 0.782312 | 5 | 68.599998 |
| (Jan01) | | | | | | | |

 $Table 2 reports final results for all pairs of taggers who double \\ -annotated four or more documents, \\ representing 30 out of the 53 documents that we redouble \\ -tagged. Results are based \\ -npre-segmented \\ documents.$

Ourteamwasabletoreachasignificantlevelofconsistency, eventhoughthey faced anumber of challenges which reflect differences in the agreements cores at the various levels. While operating under the constraint stypical of anytheoretical approach in an applied environment, the annotators faced at askin which the complexity increased as support from the guide line stended to decrease. Thus, while rules for segmenting were fairly precise, annotator srelied on heuristics requiring more human judgment to assign relations and nuclearity. Another factor is that the cognitive challenge of the task increases as the tree takes shape. It is relatively straightforward for the annotator to make a decision on assignment of nuclearity and relation at the interclause allevel, but this becomes more complex at the interclause of the task increases as the tree takes shape. It is relatively straightforward for the annotator to make a decision on assignment of nuclearity and relation at the interclause of the task increases as the tree takes shape. It is relatively straightforward for the annotator to make a decision on assignment of nuclearity and extremely difficult when linking large segments.

Thistensionbetweentaskcomplexityandguidelineunder -specificationresultedfromthepractical applicationofatheoreticalmodelonabroadscale. Whileotherdiscoursetheoreticalapproachesposit distinctly different treatments for various levels of the discourse (Van Dijkand Kintsch, 1983; Meyer, 1985), RST relies on a standard methodology to analyze the document at all levels. The RST relation set is richand the concept of nuclearity, somewhat interpretive. This gave our annotators more leeway in interpreting the higher levels of the discourse structure, thus introducing some stylistic difference which may prove an interesting a venue of future research.

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Table 2.Inter -annotatoragreement --finalresultsforsixtaggers

| | | ~ | | | | 3.7 000 | |
|---------|----------|----------|------------|-----------|-----------|-----------|------------|
| Taggers | Units | Spans | Nuclearity | Relations | Fewer- | No.ofDocs | Avg.No. |
| | | | | | Relations | | EDUs |
| B,E | 0.960384 | 0.890481 | 0.848976 | 0.782327 | 0.806389 | 7 | 88.285713 |
| A,E | 0.984471 | 0.904707 | 0.835040 | 0.755486 | 0.784435 | 6 | 57.666668 |
| A,B | 1.000000 | 0.929157 | 0.882437 | 0.792134 | 0.822910 | 5 | 58.200001 |
| A,C | 0.950962 | 0.840187 | 0.782688 | 0.676564 | 0.711109 | 4 | 116.500000 |
| A,F | 0.952342 | 0.777553 | 0.694634 | 0.597302 | 0.624908 | 4 | 26.500000 |
| A,D | 1.000000 | 0.868280 | 0.801544 | 0.720692 | 0.769894 | 4 | 23.250000 |

5. CORPUSOVERVIEW

TheRSTCorpusconsistsof385WallStreetJournalarticlesfromthePennTreebank,representing over176,000wordsoftext.Inorder tomeasureinter -annotatorconsistency,53ofthedocuments (13.8%)weredouble -tagged.Variousothercharacteristicsofthecorpusarereportedbelow:

- The documents range in size from 31 to 2124 words, with an average of 458.14 words per document.
- The finaltaggedcorpuscontains21,789EDUs(excludingthedouble -taggeddocuments).
- Theaveragenumber of EDUs perdocument is 56.59. The shortest discourse tree contains two EDUs, while the longest has 304 EDUs.
- TheaveragenumberofwordsperEDUis8.1.

Thearticlesrangeoveravariety of topics, including financial reports, general interest stories, business-relatednews, cultural reviews, editorials, and letters to the editor. In selecting these documents, we partnered with the Linguistic Data Consortiu mto select Penn Treebank texts for which the syntactic bracketing was known to be of high caliber. Thus, the RST Corpus provides an additional level of linguistic annotation to supplement existing annotated resources.

Fordetailsonobtainingthecorpus, annotationsoftware,taggingguidelines,andrelated documentationandresources,see: http://www.isi.edu/~marcu/discourse.

6. MININGTHERSTCORPU S

Agrowingnumberofgroupshavedevelopedoraredevelopingdiscourse -annotatedcorporafor text. These canb echaracterized both interms of the kinds of features annotated as well as by the scope of the annotation. Features may include specific discourse cues or markers, core ference links, identification of rhetorical relations, etc. The scope of the annotation refers to the levels of analysis within the document, and can be characterized as follows:

- *sentential*: annotationoffeaturesattheintra -sententialorinter -sententiallevel, atasinglelevel of depth(Sundheim, 1995; Tsou *et al.* 2000; Nomoto and Massumoto, 1999; Rebeyrolle, 2000).
- *hierarchical*: annotationoffeaturesatmultiplelevels, buildinguponlowerlevelsofanalysisatthe clauseorsentencelevel(MoserandMoore, 1995; Marcu *et al.* 1999)
- document-level: broadcharacterizationofdocument structuresuchasidentificationoftopical segments (Hearst, 1997), linking of large text segments via specific relations (Ferrari, 1998; Rebeyrolle, 2000), ordefining text objects with a text architecture (Pery Woodley and Rebeyrolle, 1998).

Asa hierarchicaltype, the RSTC or pusisarich resource that records an extensive and intricate human interpretation of each text, governed by detailed annotation guidelines. This interpretation lends itselfto analysis at many different levels. Below we illustrat eour own preliminary mining of the corpusat the leaf -level, text -level and mid -level. These sample analyses show how the RSTC or pus can accelerate and enrich computational analysis of discourse structure, because the researcher can extract and exploit the meta-language of the RST theory.

6.1 Leaf-LevelAnalysis:ComparisonofDiscourseMarkers

Discoursemarkershavebeenthesubjectofawiderangeofresearchbothintheoretical(Halliday and Hasan, 1976; Schriffrin, 1987; Martin 1992) and computational lin guistics (Hirschbergand Litman, 1987; Litman, 1996; Knott, 1995; Di Eugenio, Moore, and Paolucci, 1997; Marcu 2000).

Thoughon -linecorporahavefacilitatedempiricalinvestigationsoftheroleofdiscoursemarkersin textanalysisandgeneration,noneo fthepreviousempiricalworkcouldtakeadvantageofacorpusas richastheonewebuilt —manyempiricalanalyseswerecarriedoutwithnoaccesstohierarchical annotationsofunderlyingtexts(Knott,1995;Marcu2000)orwithaccesstoarelativelysm allcorpus ofhierarchicallyannotatedstructures(DiEugenio,Moore,andPaolucci,1997).

HavingtheRSTCorpusalreadyannotated and interpreted by human analysts allows the computational linguist to perform a level analysis of discourse cues in multiple contexts. We examined two discourse markers, since and as, to explore their distribution in the RST - annotated corpus. The meta - language of the corpus gave us ready access to information about frequency, rhetorical relation, nuclearity, and other aspects of these cues. Table 3 summarizes the distribution of these cues in the training corpus (347 documents; 157,930 words).

| Table 3. Comparison of discourse mar | kers sinceand as | |
|--------------------------------------------|------------------|-----|
| | since | as |
| #ofoccurrencesofwordintrainingcorp us | 128 | 730 |
| #ofoccurrencesthattriggerdiscourserelation | 42 | 240 |
| #ofdifferentrelationsselected | 10 | 25 |
| Nuclearityofdiscoursemarker: | | |
| #innucleus(mononuclearcase) | 11 | 9 |
| #insatellite | 35 | 205 |
| #innucleus(multinuclearcase) | 6 | 26 |
| Positionof discoursemarker: | | |
| #infirstspanofrelation | 14 | 48 |
| #insecondspanofrelation | 28 | 192 |
| | | |

| | since | as |
|----------------------|-------|-----|
| Scopeofrelation: | | |
| #ofinter -clausal | 36 | 225 |
| #ofinter -sentential | 3 | 10 |
| #ofmulti -sentential | 3 | 5 |

Theinformationextractedrevealsanumberofproperties of these markers. The first observation is that relative to the frequency of these words in the corpus, they only triggered a discourse relation in about one third of the cases. This is because as and since were not always factors in relating two EDUs, as defined in our annotation guidelines. Instead, the terms frequently performed a function at the propositional level, rather than the discourse level. For example:

- Thetermsinceoftenappearedinatemporalphrase:"...,saysScottC.Newquist,Kidder'shead of investmentbankingsinceJune."(wsj 0604)
- The term *as* often occurred as a phrasal complement of a main verb: "to serve, a mongother things, as the court of last resort for most patent disputes." (wsj_0601)

Asecondobservationisthatthesemarkerstr iggeralargenumberofdifferentrhetoricalrelations, with astriggeringamuchbroaderrangeofrelationsthan since.³ Abreakdownofthedistributionofthese markersacrosstheinventoryofrhetoricalrelationsisshowninTable4. Thirdly, Table3sh owsthat whenthesetermsdidappearasdiscoursemarkers, theyoccurredamajorityofthetimeinthesatellite (83% for since;85% for as), and in the second span of the relation (67% for since;80% for as). Most significantly, we documented that the sed is coursemarkers almost always trigger local relations: for since, 86% of the cases are inter -clausal, and, for as, 94%.

Inshort, our initial analysis of an umber of factors — frequency of occurrence, triggers for discourse relation, types of relationse lected, scope of relation across multiple EDUs, nuclearity and span position—demonstrated a limited, and rather local, discourse function for since and as. In the following two sections, we illustrate how we exploit the meta—language of the annotated discourse trees to examine the higher and middle levels of the discourse structure.

| Table 4.Comparisonofrelat | since and as | |
|---------------------------|--------------------|-----------------|
| RelationName | Frequencyfor since | Frequencyfor as |
| analogy | | 8 |
| antithesis | 1 | 1 |
| attribution | | 18 |
| background | | 1 |
| cause-result | | 2 |
| circumstance | 14 | 69 |
| comment | | 5 |
| comparison | | 24 |
| concession | | 1 |
| conclusion | 1 | |
| condition | | 5 |
| consequence-n | 1 | 9 |
| consequence-s | | 3 |
| contingency | | 2 |
| elaboration-additional | 1 | 15 |
| evaluation-s | | 1 |
| evidence | | 1 |
| example | | 1 |
| explanation-argumentative | 3 | 10 |
| interpretation-s | | 1 |
| list | | 4 |
| manner | | 10 |
| means | | 1 |

³Forthispreliminaryanalysis, allcases of asthattriggereddiscourse relationswer ecounted, including the following phrasals: aslongas, assoonas, asif, as are sult

| RelationName | Frequencyfor since | Frequencyfor as |
|--------------------|--------------------|-----------------|
| reason | 5 | 1 |
| result | 1 | 18 |
| sequence | 4 | 1 |
| temporal-after | 7 | |
| temporal-before | | 1 |
| temporal-same-time | | 26 |
| topic-drift | 1 | |
| spurious | 3 | 1 |

6.2 Text-LevelAnalysis:Com parisonofTreesforDifferentStylesofNews Reports

Therearefewcommunityresourcesavailablethatcapturetext -levelcharacteristicsasidefrom genreorregister, asinthe Lancaster -Oslo/Bergen Corpus (Garside etal. 1987; Biber etal. 1998), or topicidentification, asinthe TDT Corpus (Wayne, 2000). The RST Corpus, incontrast, presents a multi-level discourse representation of the entirer hetorical structure of each document. The highest level of a discourse tree depicts the organization of thete xtandserves as ar hetorical outline. This view of the document is constrained by a finite set of rhetorical relations, the use of which is governed by the annotation guidelines. The tree may be viewed graphically at varying levels of depth. At the most a bstractlevel, the tree provides a non-lexical or rhetorical summary of the content defined by the relations and hierarchical branching structure. Zooming in on any non-leaf node reveals concrete details of the rhetorical structure.

Weselectedthreerepre sentativestylesofnewstextsforcomparisonoftext -levelcharacteristics.In eachfigure,theupperpaneoftheRSTStructurertooldisplaysthehighestlevelofatextandthelower panepresentsaportionofthetext(withEDUboundariesmarked)that correspondstotextspansinthe tree.

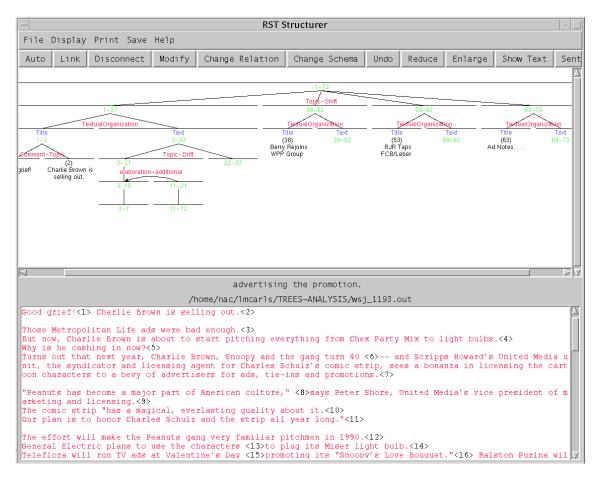


Figure 2.TopLevelDiscourseTreeforDocument#1193:highlystructuredwithtopicshifts

Document#1193(Figure2)isagoodexampleofahighlystructureddocument ,composedofa seriesofnewsbriefswithclearlymarkedheadingsandsections. Therhetoricalrelation TOPIC-SHIFT linksthesub -sectionsofthedocument, eachofwhichisactuallyaseparatenewsstory. At the subsequentlevel, each story contains a TITLE and TEXT section -the selabelsare schemata, which refer to structural elements of theorganization of the text. Schemata are associated within dividual nodes in the discourse structure of a text, and represent an annotation level that is independent of the rhetorical relations. Schemata donot reflect relations between text spans, but rather characterize a functional role of an individual text span. The TEXTUAL-ORGANIZATION relation is used to link two or more spans labelled asschemata.

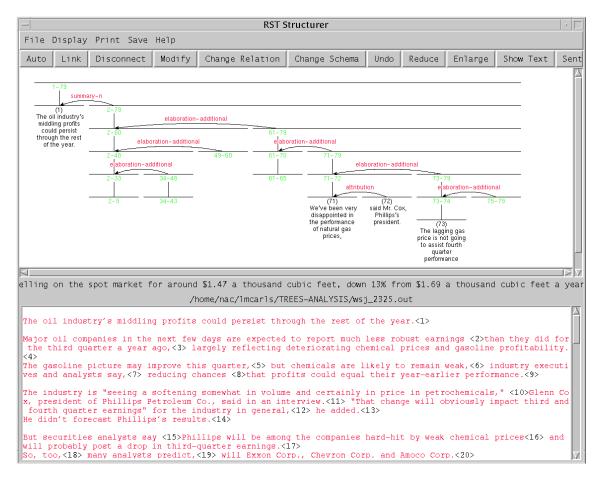
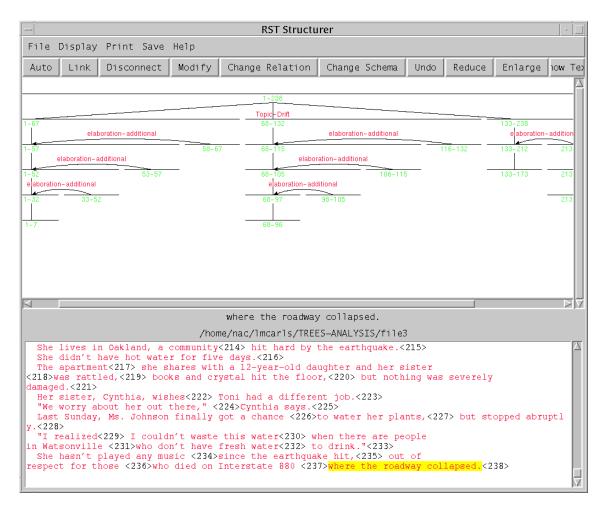


Figure 3.TopLevelDiscourseTreeforDocument#2325:Summaryleadfollowedbysupportingdetails

Document#2325(Figure3)typifiesthejournalisticpracticeofabusinessnewsarticlewithan initialsummaryleadfollowedby supportingdetails. This style is representative of a larger portion of the corpusthan Document#1193. Herethetextis formed by a series of successive texts pans that elaborate on the summary sentence. The highlevels napshot shows how the text is chunk edintotext segments that expandupon the content at different levels.



Figure~4. Top Level Discourse Tree for Document # file 3: less structured, with topic drifts

Thehigh -leveldiscoursestructureofDocument#fil e3(Figure4)outlinesadocumentthat illustratesa TOPIC-DRIFTstyle:Ahuman -intereststoryiswovenaroundanexpositorytextdetailing theimpactoftheSanFranciscoearthquakeontheinsurancetrade.Thetextbeginswithanon -thescenedescription ofaninsuranceclaimsadjusterassessingdamagestoahousedestroyedbytheSanFranciscoearthquake,switchestoageneraldescriptionoftheimpactontheinsurancetrade,andthen returnstothepersonalexperienceoftheadjuster.Thedocumentisam ixtureofexpositoryand narrativestyles,whichtaxestheannotatorbecauseofitslackofovertstructure.

WebelievethattheRSTCorpuscansupportthediscoveryofnewlinesofinquiryatthetextlevel.

TheRSTCorpusenablestheresearchertoinven torythemechanismsusedtoorganizethetextatthe highestlevelwithinthecontextofasingletheory. It is available for exploring rhetorical strategies for generating text, discovering the degree of variation intextorganization, and comparing RST toother theoretical approaches for representing the high revelent to revele the torical structure of documents.

6.3 Mid-LevelAnalysis:ExaminationofRelations

Wedefinethemid -leveldiscoursestructuretobeanymulti -sententialsegmentofthetextthatis capturedbya particularrhetoricalrelation,butisnotdominateddirectlybytherootnodeora TEXTUALORGANIZATIONrelation.

TakingasecondlookatthedocumentscharacterizedatthetextlevelinSection6.2,thereaderwill noticethefrequentuseof ELABORATION-ADDITIONALasarhetoricaldevic efororganizinglarge

segmentsofthedocumentattheuppermiddlelevelofthediscourse. Thisoccursinallthreeofthetext stylesdescribed. Although the total inventory of relations is quite extensive, one of themos frequently occurring relations ets in the RST Corpusis elaboration (see Section 2.2), because a typical rhetorical strategy is for the writer to expand on the previous context. Thus, the relation ELABORATION-ADDITIONAL became a defactode fault whenever a more semantically marked relation did not fit the context.

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Thereare,however,numerousoccurrencesofothermulti -sententialrhetoricalrelationsthatare characteristicofthemid -levelofthediscourse. Abriefinvestigation of two very different ty pesof rhetorical relations - LIST and INTERPRETATION - will illustrate to the reader the potential utility of the corpus for analysis at the mid -level of the discourse.

Inthecorpusannotationguidelines,a LISTrelationisdefinedas"amultinuclearre lationwhose elementscanbelisted,butwhicharenotinacomparison,contrastorother,strongertypeof multinuclearrelation.A LISTrelationusu allyexhibitssomesortofparallelstructurebetweentheunits involvedintherelation."Automaticiden tificationofa LISTstructureistrivialwhentheelementsare enumeratedorsignalledbysomeotherovertformattingcharacteristicsuchasindentation.However, veryofteninthecorpus,a LISTrelationwasapparenttotheannotatorbecauseofsomesort ofparallel syntacticorsemanticstructurebetweentheunitsofthetext,asinFigure5.Here,the LISTstructure wasselectedbecauseofseveralfeatureswhich,takentogether,createacomplexparallel

- 1. Eachelementofthe LISTpresents oneexampleofcontrastbetweentwoexecutives, e.g., comes acrossasalow -keyexecutive vs. hasaflashierpersonality .
- 2. Each CONTRASTrelationinthe LISTisstructuredasacompoundsentencewiththeelements separatedbyasemi -colon;bothconjoinsco ntainasingleclauseintheactivevoice.
- 3. Thenames *Mr.Roman* and *Mr.Phillips*occurinaparallelmannerinthetwolistedelements,each asthesubjectofoneofthetwoconjoins,andinthesameorderforbothitemsinthe LIST.

Eitherbranchofthiss ub-treeillustrateshowparallelstructuresformacohesivedevice(Halliday andHasan,1976). Together, they create aparallel text substructure. We have observed that this phenomenon occurs not only with the LIST relation, but also with other multinuclea rrelations, such as PROBLEM-SOLUTION, QUESTION-ANSWER, CONTRAST, and so on. The richand varying set of such examples explicitly annotated in the corpuscreates an opportunity to explore the phenomenon of textual parallelism, with potential application various language processing applications, such as text generation or machine translation.

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⁴Analysisatthislevelisanalogoustoresearchconductedonarangeofdiscoursephenomena, suchasanaphoric relations (Garside *et al* .1997), or speech and dialog acts (Levin *et al* .1998).

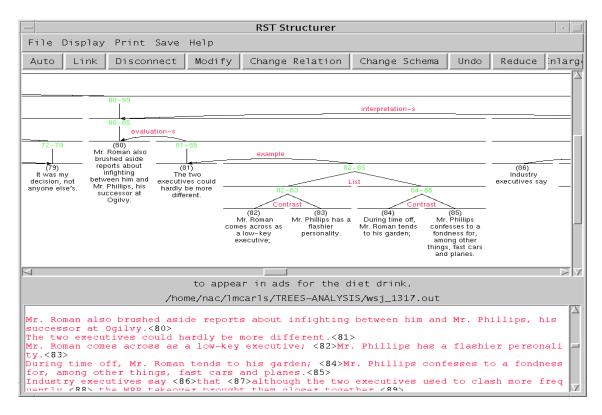


Figure 5. LISTrelationwithparallelsyntacticandsemanticstructure

Anotherinsightintoanalysisofthemid -leveldisco ursestructurecomesfromthediscoverythat subjectiverelationssuchas INTERPRETATIONareinterspersedthroughouttheRSTCorpus, which consistsprimarilyofexpositorynewstexts. Surprisingly, evenwhen annotators disagree on the specific nature of the esubjective relation ⁵, they consistently and easily identify the segments of the text that are subjective in nature. Below is a sample text fragment from Document #0628, which contains numerous subjective passages, two of which are shown here in italics:

Machine tool executives are hopeful, however, that recent developments in Eastern Europe will expand markets for U.S. -made machine tools in that region.

There is demand for state -of-the-art machine tools in the Soviet Union and in other Eastern European c ountries as those nations strive to improve the efficiency of their ailing factories as well as the quality of their goods.

However, there's a continuing dispute between machine tool makers and the Defense Department over whether sophisticated U.S. machine tools would increase the Soviet Union's military might. "The Commerce Department says go, and the Defense Department says stop," complains one machine tool producer.

⁵Otherexamplesofsubjectiverelationsfoundinthecorpusare

If that controversy continues, U.S. machine tool makers say, West German and other fore ign producers are likely to grab most of the sales in Eastern Europe.

The discourse tree for this portion of Document #0628 is shown in Figure 6. Note how the subjectivepassagescorrespondtotheselectionofan INTERPRETATION relation by the annotator. I firstcase,theannotatorhaschosentomarkspan[38 -39lasthesatelliteofan INTERPRETATION relation.Thelabelledarc INTERPRETATION-Spointstothenucleusoftherelation, span [40] -41],and indicatesthattheinterpretationoccursinthesatel lite.Inthesecondcase,theannotatordecidesthatthe -47],andselects interpretativetext,span[48] -50],ismoresalientthanthesatellite,span[42] INTERPRETATION-Nastherelation. Accesstoour data will raise the barfor analysis of more complex linguisticphenomenarelatedtosubjectivityinwriting.

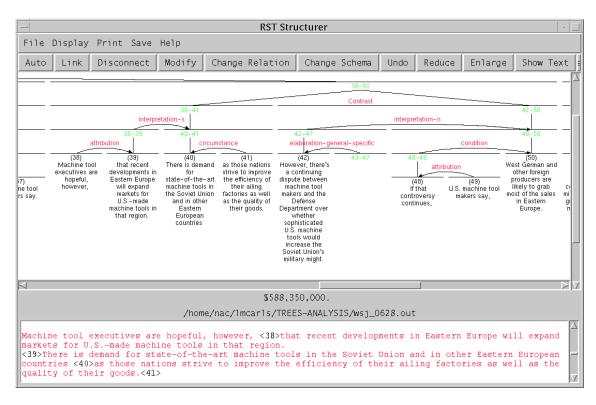


Figure 6. Subjectivity intextmarked by INTERPRETATION relation

7. CONCLUSIONSANDFUTU REWORK

Developingcorporawiththesekindsofrichannotationisalab or-intensiveeffort.Buildingthe RSTCorpusinvolvedmorethanadozenpeopleonafullorparttimebasisoveraone -yeartimeframe (Jan-Dec2000).Annotationofasingledocumentcouldtakeanywherefrom30minutestoseveral hours,dependingonthele ngthandtopic.Re -taggingalargenumberofdocumentsaftermajor enhancementstotheannotationguidelineswasalsotimeconsuming.Notwithstandingoureffortto ensurethequalityofthefinaldiscoursecorpusanddemonstrationofrelativelyhighinter -annotator agreement,weexpectthatresearcherswillidentifyanomaliesintheRSTCorpus,astypicalofall

annotationefforts. Webelievethat some subset of these can be tracked to simple errors. For example, an annotator accidentally highlights the wro ngrelation in a list or mis assigns nuclearity.

Alargerissue, though, stems from variation in stylistic interpretation among annotators. The RST theorydoesnotdifferentiatebetweendifferentmicro -andmacro -levelsofthediscoursestructure, and thus, afairly fine -grainedsetofrelationsoperatesatalllevels. This, along with the concept of nuclearity, increased the variation in annotator interpretation. Even though we had very well defined rules for segmenting the text into EDUs, it proved quite difficulttomakeouralreadyextensive guidelinesmoreexplicitindictatinghowtoassignnuclearityandrelations.Otherresearchers(Ferrari, -levelrelationsfortextsegments, or have conducted 1998; Meyer, 1985) have posited a few macro studiesona muchmorelimitedsetofrelations(Rebeyrolle, 2000). This approach has the advantage of limiting variability in annotation. However, our goal was to conduct a large -scaleimplementation withintheframeworkofasinglediscoursetheoryinitsentirety, withtheexpectationthatthiswould allowforabetterassessmentofbothitsstrengthsanditslimitations. Webelievethattheannotated corpusitself, along with the subset of documents with double annotations, will lead to refine ments in theRSTtheor v.

Basedonourhands -onworkandinitialanalysisofthissubstantialcorpus, weanticipatethatthe RSTCorpuswillbemultifunctional and supportawiderange of language engineering applications. The added value of multiple layers of overtlinguistic henomena en hancing the Penn Treebank information can be exploited to advance the study of discourse, to en hance language technologies such astext summarization, text generation, machine translation or information retrieval, or to provide a test bed for new and creative natural language processing techniques.

ACKNOWLEDGEMENTS

Wewouldliketoacknowledgethesignificantcontributionsoftheannotatorswhoparticipatedin thetaggingofthiscorpusandinpriortaggingexperimentsthatleddirectlytothisef fort.Withouttheir dedicationandkeeninsights,thisworkwouldnothavebeenpossible: EstibalizAmorrortu,Jean Hobbs,JohnKovarik,TobyMerriken,NorbRieg,MagdalenaRomera,MakiWatanabe,andMarkell West.

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