BuildingaDiscourse -TaggedCorpusintheFrameworkof RhetoricalStructureTheory

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Abstract

Wedescribeourexperiencein developingadiscourse -annotated corpusforcommunity -wideuse. Workingintheframeworkof RhetoricalStructureTheory, wewere abletocreatealargeannotated resourcewithvervhighconsistency. usingawell -definedmethodologyand protocol. This resource is made publiclyavailablethroughthe LinguisticDataConsortiumtoenable researcherstodevelopempirically grounded.discourse -specific applications.

1 Introduction

Theadventoflarge -scalecollectionsof annotateddatahasmarkedaparadigmshiftin theresearchcommunityfornaturallanguage processing. These corpora, now also common in manylanguages, have accelerated development effortsandenergizedthecommunity. Annotationrangesfrombroadcharacterization ofdocument -levelinformation, such a stopic or relevancejudgments(VoorheesandHarman, 1999; Wayne, 2000) to discrete analys widerangeoflinguisticphenomena. However, rich theoreticalapproachestodiscourse/text analysis(VanDijkandKintsch, 1983; Meyer, 1985; Groszand Sidner, 1986; Mannand Thompson, 1988) have yet to be applied on a largescale.Sofar,theann otationofdiscourse structureofdocumentshasbeenapplied primarilytoidentifyingtopicalsegments (Hearst, 1997), inter -sententialrelations (NomotoandMatsumoto,1999;Ts'ouetal., 2000), and hierarchical analyses of small

corpora(MoserandMoore, 1995;Marcuetal., 1999).

Inthispaper, we recount our experience in developingalargeresourcewithdiscourse -level annotationforNLPresearch.Ourmaingoalin undertakingthiseffortwastocreateareference corpusforcommunity -wideuse.Twoesse ntial considerations from the outset were that thecorpusneededtobeconsistentlyannotated,and thatitwouldbemadepubliclyavailablethrough theLinguisticDataConsortiumforanominal feetocoverdistributioncosts. The paper describesthechalle ngeswefacedinbuildinga corpusofthislevelofcomplexityandscope including selection of theoretical approach, annotationmethodology, training, and quality assurance. The resulting corpus contains 385 documentsofAmericanEnglishselectedfrom thePennTreebank(Marcusetal.,1993), annotatedintheframeworkofRhetorical StructureTheory.Webelievethisresource holdsgreatpromiseasarichnewsourceoftext levelinformationtosupportmultiplelinesof researchforlanguageunderstanding applications.

2 Framework

Twoprinciplegoalsunderpinthecreationofthis discourse-taggedcorpus:1)Thecorpusshould begroundedinaparticulartheoreticalapproach, and2)itshouldbesufficientlylargeenoughto offerpotentialforwide -scaleuse -including linguisticanalysis,trainingofstatisticalmodels ofdiscourse,andothercomputationallinguistic applications. Thesegoalsnecessitatedanumber ofconstraintstoourapproach. Thetheoretical frameworkhadtobepracticalandrepeatable overalargesetofdocumentsinareasonable amountoftime, withasignificantlevelof consistencyacrossannotators. Thus, our

approachcontributestothecommunityquite differentlyfromdetailedanalysesofspecific discoursephenomenaindepth,suchas anaphoricrelations(Garsideetal.,1997)or styletypes(Leechetal.,1997);analysisofa singletextfrommultipleperspectives(Mann andThompson,1992);orillustrationsofa theoreticalmodelonasinglerepresentativetext (BrittonandBlack,198 5;VanDijkandKintsch, 1983).

Ourannotationworkisgroundedinthe RhetoricalStructureTheory(RST)framework (MannandThompson,1988).Wedecidedto useRSTforthreereasons:

- Itisaframeworkthatyieldsrichannotations thatuniformlycaptureint entional,semantic, andtextualfeaturesthatarespecifictoa giventext.
- Previousresearchonannotatingtextswith rhetoricalstructuretrees(Marcuetal., 1999)hasshownthattextscanbeannotated bymultiplejudgesatrelativelyhighlevels ofagr eement.Weaimedtoproduce annotationprotocolsthatwouldyieldeven higheragreementfigures.
- PreviousresearchhasshownthatRSTtrees canplayacrucialroleinbuildingnatural languagegenerationsystems(Hovy,1993; MooreandParis,1993;Moore,1 995)and textsummarizationsystems(Marcu,2000); canbeusedtoincreasethenaturalnessof machinetranslationoutputs(Marcuetal. 2000);andcanbeusedtobuildessay scoringsystemsthatprovidestudentswith discourse-basedfeedback(Bursteineta 2001). WesuspectthatRSTtreescanbe exploitedsuccessfullyinthecontextof otherapplicationsaswell.

IntheRSTframework, the discourse structure of a text can be represented a satree defined in terms of four aspects:

- Theleavesofthetree correspondtotext fragmentsthatrepresenttheminimalunits ofthediscourse, called elementary discourseunits
- Theinternalnodesofthetreecorrespondto contiguoustext *spans*
- Eachnodeischaracterizedbyits *nuclearity* –anucleusindicatesamore essentialunitof information, whileasatelliteindicatesa

- supportingorbackgroundunitof information.
- Eachnodeischaracterizedbya rhetorical relationthatholdsbetweentwoormore non-overlapping,adjacenttextspans.
 Relationscanbeofintentio nal,semantic,or textualnature.

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

2.1 SegmentingTextsintoUnits

Thefirststepincharacterizingthediscourse structureofatextinourprotocolistodetermine theelement arydiscourseunits(EDUs), which aretheminimalbuildingblocksofadiscourse tree.MannandThompson(1988,p.244)state that"RSTprovidesageneralwaytodescribe therelationsamong clauses in a text, whether or nottheyaregrammaticallyorlexic ally signalled."Yet,applyingthisintuitivenotionto thetaskofproducingalarge, consistently annotatedcorpusisextremelydifficult, because theboundarybetweendiscourseandsyntaxcan beveryblurry. The examples below, which rangefromtwodist inctsentencestoasingle clause, all conveyes sentially the same meaning, packagedindifferentways:

- 1. [XeroxCorp.'sthird -quarternetincome grew6.2%on7.3%higherrevenue.][This earnedmixedreviewsfromWallStreet analysts.]
- 2. [XeroxCorp'sthird -quarternetincome grew6.2%on7.3%higherrevenue,][which earnedmixedreviewsfromWallStreet analysts.]
- 3. [XeroxCorp'sthird -quarternetincome grew6.2% on 7.3% higherrevenue,] [earning mixed reviews from Wall Street analysts.]
- 4. [The6.2% growthofXer oxCorp.'sthird quarternetincomeon7.3% higherrevenue earnedmixedreviews from Wall Street analysts.]

In Example 1, there is a consequential relation between the first and second sentences. Ideally, we would like to capture that kind of rhetorical in formation regardless of the syntactic form in which it is conveyed. However, as examples 2 -4 illustrate, separating rhetorical

fromsyntacticanalysisisnotalwayseasy. Itis inevitablethatanydecisiononhowtobracket elementarydiscourseunitsneces sarilyinvolves some compromises.

Reseachersinthefieldhaveproposeda numberofcompetinghypothesesaboutwhat constitutes an elementary discourse unit. While sometaketheelementaryunitstobeclauses (Grimes, 1975; Givon, 1983; Longacre, 1983), otherstakethemtobeprosodicunits (HirschbergandLitman, 1993), turnsoftalk (Sacks, 1974), sentences (Polanyi, 1988), intentionally defined discourse segments (Grosz andSidner,1986),orthe"contextuallyindexed representationofinformationconveye semioticgesture, asserting a single state of affairsorpartialstateofaffairsinadiscourse world,"(Polanyi,1996,p.5).Regardlessoftheir theoretical stance, all agree that the elementary discourseunitsarenon -overlappingspansof

Ourgoalwastofindabalancebetween granularityoftaggingandabilitytoidentify unitsconsistentlyonalargescale.Intheend, wechosetheclauseastheelementaryunitof discourse,usinglexicalandsyntacticcluesto helpdetermineboundaries:

- [AlthoughMr.Freemanisretiring,][hewill continuetoworkasaconsultantfor AmericanExpressonaprojectbasis.] wsj_1317
- 6. [BondCorp.,abrewing,property,media andresourcescompany,issellingmanyof itsassets][**toreduce** itsdebts.] wsi 0630

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

- 7. [Makingcomputerssmaller oftenmeans sacrificingmemory.]_{wsi_2387}
- 8. [Insurerscouldseeclaims totalingnearly \$1billionfromtheSanFrancisco earthquake.]_{wsj_0675}

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

- 9. [TheresultsunderscoreSears'sdifficulties] [inimplementingthe"everydaylow pricing"strategy...]_{wsi_1105}
- 10. [TheBushAd ministration,][tryingtoblunt growingdemandsfromWesternEuropefor

arelaxationofcontrolsonexportstothe Sovietbloc, [[isquestioning...] wsi 2326

Finally,asmallnumberofphrasalEDUsare allowed,providedthatthephrasebeginswitha strongdi scoursemarker,suchas because,in spiteof,asaresultof,accordingto .Weopted forconsistencyinsegmenting,sacrificingsome potentiallydiscourse -relevantphrasesinthe process.

2.2 BuildinguptheDiscourseStructure

Oncetheelementaryunitsofdi scoursehave beendetermined, adjacents pansarelinked togetherviarhetoricalrelationscreatinga hierarchicalstructure.Relationsmaybe mononuclearormultinuclear. Mononuclear relationsholdbetweentwospansandreflectthe situationinwhichones pan,the nucleus,ismore salienttothediscoursestructure, while the other satellite, represents supporting span,the information.Multinuclearrelationsholdamong twoormorespansofequalweightinthe discoursestructure. Atotalof 53 mononuclear and25multinuclearrelationswereusedforthe taggingoftheRSTCorpus.Thefinalinventory ofrhetoricalrelationsisdatadriven, andis basedonextensiveanalysisofthecorpus. Althoughthis inventory is highly detailed, annotatorsstronglypreferr edkeepingahigher levelofgranularityintheselectionsavailableto themduring the tagging process. More extensive analysisofthefinaltaggedcorpuswill demonstratetheextenttowhichindividual relationsthataresimilarinsemanticcontent were distinguishedconsistentlyduringthe taggingprocess.

The 78 relations used in annotating the corpuscanbepartitionedinto16classesthat sharesometypeofrhetoricalmeaning: Attribution, Background, Cause, Comparison, Condition, Contrast, Elaboratio n, Enablement, Evaluation, Explanation, Joint, Manner - Means, Topic-Comment, Summary, Temporal, Topic-Change. For example, the class Explanation evidence, explanation includestherelations argumentative, andreason, while *Topic* Comment includesproblem -solution, question answer, statement -response, topic -comment, and comment-topic. Inaddition, three relations are usedtoimposestructureonthetree: organization, span, and same-unit (used to link

partsofunitsseparated by embedded units or spans).

3 DiscourseAnnotationTask

OurmethodologyforannotatingtheRST
Corpusbuildsonpriorcorpusworkinthe
RhetoricalStructureTheoryframeworkby
Marcuetal.(1999).Becausethegoalofthis
effortwastobuildahigh -quality,consistently
annotatedreferencecorpus,thetaskrequired
thatweemploypeopleasannotatorswhose
primaryprofessionalexperiencewasinthearea
oflanguageanalysisandreporting,provide
extensiveannotatortraining,andspecifya
rigoroussetofannotationguidelines.

3.1 AnnotatorProfileandTraining

Theannotatorshiredtobuildthecorpuswereall professionallanguageanalystswithprior experienceinothertypesofdataannotation. Theyunderwentextensivehands -ontraining, whichtookplaceroughlyinthreephases. Duringtheorientationphase, the annotators wereintroducedtotheprinciplesofRhetorical StructureTheoryandthediscourse -taggingtool usedfortheproject(Marcuetal., 1999). The toolenablesanannotatortosegmentatextinto units, and then build upahierarchical structure ofthediscourse.Inthisstageofthetraining,the focuswasonsegmentinghardcopytextsinto EDUs, and learning the mechanics of the tool.

Inthesecondphase, annotators began to exploreinterpretationsofdiscoursestru cture, by independentlytaggingashortdocument,based onaninitialsetoftaggingguidelines, and then meetingasagrouptocompareresults. The initialfocuswasonresolvingsegmentation differences, but overtimethis shifted to addressingissuesof relationsandnuclearity. These exploratorys essions led to enhancements inthetaggingguidelines.Toreinforcenew rules.annotatorsre -taggedthedocument. Duringthisprocess, were gularly tracked inter annotatoragreement(seeSection4.2).Inthe finalphase, the annotation team concentrated on waystoreducedifferencesbyadoptingsome heuristicsforhandlinghigherlevelsofthe discoursestructure. Wiebeetal. (1999) present amethodforautomaticallyformulatingasingle judgesdisagreeon besttagwhenmultiple selectingbetweenbinaryfeatures.Becauseour annotatorshadtoselectamongmultiplechoices

ateachstageofthediscourseannotation process, and because decisions made at one stage influenced the decisions made during subsequents a ges, we could not apply Wiebe et al.'s method. Our methodology for determining the "best" guidelines was much more of a consensus-building process, taking into consideration multiple factors at each step. The final tagging manual, over 80 pages in length, contains extensive examples from the corpusto illustrate texts egmentation, nuclearity, selection of relations, and discourse cues. The manual can be downloaded from the following website: http://www.isi.edu/~marcu/discourse.

Theactualtaggingofthec orpusprogressed inthreedevelopmentalphases. During theinitial phase of about four months, the team created a preliminarycorpusof100taggeddocuments. Thiswasfollowedbyaone -monthreassessment phase, during which we measured consistency acrosst hegrouponaselectsetofdocuments, andrefinedtheannotationrules. Atthispoint, wedecidedtoproceedbypre -segmentingallof thetextsonhardcopy,toensureahigheroverall qualitytothefinalcorpus. Eachtextwaspre segmentedbytwoannota tors; discrepancies wereresolvedbytheauthorofthetagging guidelines.Inthefinalphase(aboutsixmonths) all100documentswerere -taggedwiththenew approachandguidelines. Theremainder of the corpuswastaggedinthismanner.

3.2 TaggingStrategi es

Annotatorsdevelopeddifferentstrategiesfor analyzingadocumentandbuildingupthe corresponding discourse tree. The rewere two basicorientationsfordocumentanalysis -hard copyorgraphicalvisualizationwiththetool. Hardcopyanalysisranged fromjottingofnotes inthemarginstomarkingupthedocumentinto discoursesegments. Thosewhopreferreda graphicalorientationperformedtheiranalysis simultaneouslywithbuildingthediscourse structure, and were more likely to build the treeinchunks.ratherthan discourse incrementally.

Weobserved avariety of annotation styles for the actual building of a discourse tree. Two of the more representative styles are illustrated below.

1. Theannotatorsegmentsthetextoneunitat atime,thenincrem entallybuildsupthe

discoursetreebyimmediatelyattachingthe currentnodetoapreviousnode .When buildingthetreeinthisfashion,the annotatormustanticipatetheupcoming discoursestructure, possibly for a large span. Yet, often an appropriate choiceof relationforanunseensegmentmaynotbe obviousfromthecurrent(rightmost)unit thatneedstobeattached. That is why annotatorstypicallyusedthisapproachon shortdocuments, but resorted to other strategies for longer documents.

2. Theanno tatorsegmentsmultipleunitsata time.thenbuildsdiscoursesub -treesfor eachsentence.Adiacentsentencesarethen linked,andlargersub -treesbeginto emerge.Thefinaltreeisproducedby linkingmajorchunksofthediscourse

Corp.]¹⁸[Thisisinpartbecauseoftheeffect] [ofhavingtoaveragethenumberofshares outstanding,]²⁰[sh esaid.] ²¹[Inaddition,] ²²[Mrs. Lidgerwoodsaid,] ²³[Norfolkislikelytodraw downits cashinitially] ²⁴[tofinancethe purchases]²⁵[andthusforfeitsomeinterest income.]²⁶ wsi 1111

The discourse sub -tree for this text fragment isgiveninFigure1 . UsingStyle1theannotator, uponsegmentingunit[17],mustanticipatethe upcoming examplerelation, which spansunits [17-26]. However, even if the annotator selects anincorrectrelationatthatpoint, the toolallows greatflexibilityinchangingth estructureofthe treelateron.

UsingStyle2,theannotatorsegmentseach sentence, and build supcorresponding sub -trees forspans[16],[17 -18],[19 -21]and[22 -26].The

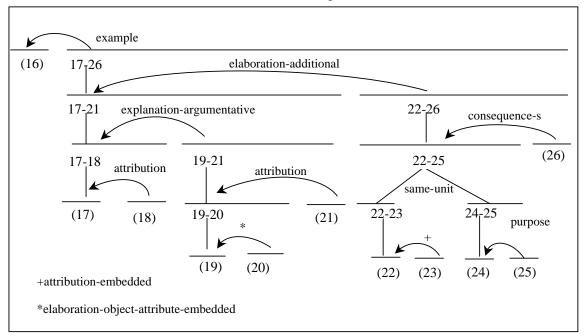


Figure 1: Discoursesub -treeformultiplesentences

structure. This strate gyallows the annotator toseetheemergingdiscoursestructuremore globally; thus, it was the preferred approach forlongerdocuments.

Considerthetextfragmentbelow, consisting offoursentences, and 11EDUs:

-backto [Still,analystsdon'texpectthebuy significantly affectper -share earning sin the shortterm.] ¹⁶[Theimpactwon'tbethatgreat,] [saidGraemeLidgerwoodofFirstBoston

secondandthirdsub -treesarethenlinkedviaan explanation-argumentative relation, afterwhich, thefourthsub -treeislinkedviaan elaborationadditionalrelation. The resulting span [17] -26]is finallyattachedtonode[16]asan example satellite.

4 QualityAssurance

Anumberofstepsweretakentoensurethe qualityofthefina ldiscoursecorpus. These

Table1:Inter -annotatoragreement -periodicresultsforthreetaggers

Taggers	Units	Spans	Nuclearity	Relations	Fewer-	No.of	Avg.No.
					Relations	Docs	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)							

involvedtwotypesoftasks:checkingthe validityofthetreesandtrackinginter -annotator consistency.

4.1 TreeValidationProcedures

Annotatorsreviewedeachtreeforsyntacticand semanticvalidity. Syntacticchecking involved ensuring that the tree hadas in gleroot node and comparing the tree to the document to check for missing sentences or fragments from the end of the text. Semanticchecking involved reviewing nuclearity assignments, as well as choice of relation and level of attachment in the tree. All trees were checked with a discourse parser and tree travers alprogram which of ten identified errors undetected by the manual validation process. In the end, all of the trees worked successfully with the seprograms.

4.2 MeasuringConsistency

Wetrackedinter -annotatoragreementduring eachphaseoftheproject, using amethod developed by Marcuetal. (1999) for computing kappastatistics overhier archical structures. The kappacoefficient (Siegeland Castellan, 1988) has been use dextensively in previous empirical studies of discourse (Carletta et al., 1997; Flammia and Zue, 1995; Passonne au and Litman, 1997). It measures pairwise agreement among a set of coders who make category judgments, correcting for chance expected agreement. The method described in Marcuet al. (1999) mapshier archical structures into sets of units that are labeled with categorial

judgments. The strengths and short comings of the approach are also discussed in detail there. Researchers in content analysis (Kr ippendorff, 1980) suggest that values of kappa>0.8 reflect very high agreement, while values between 0.6 and 0.8 reflect good agreement.

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

Attheunitlevel,theinitial(April00)scores andfinal(January01)scoresrepresent agreementonblindsegmentation.andare showninboldface.TheinterimJuneand Novemberscoresrepresentagreementonhard copypre -segmentedtexts. Notice that even with pre-segmenting, the agreement on units is not 100% perfect, because of human errors that occurinsegmentingwiththetool.AsTable1 shows, all levels demonstrate a marked improvementfromApriltoNovember(when thefinal corpuswascompleted),rangingfrom about 0.77 to 0.92 at the spanlevel, from 0.70 to 0.88atthenuclearitylevel,andfrom0.60to 0.79attherelationlevel.Inparticular, when relations are combined into the 16 rhetorically related classes discussed in Section 2.2, the Novemberresultsoftheannotationprocessare extremelygood. The Fewer -Relationscolumn showstheimprovementinscoresonassigning

Table2:Inter -annotatoragreement -finalresultsfoxsixtaggers

Taggers	Units	Spans	Nuclearity	Relations	Fewer-	No.of	Avg.No.
					Relations	Docs	EDUs
В,Е	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

relationswhentheyaregroupedinthismanner, withNovemberresultsrangingfrom0.78to 0.82.In ordertoseehowmuchofthe improvementhadtodowithpre -segmenting,we askedthesamethreeannotatorstoannotatefive previouslyunseendocumentsinJanuary. withoutreferencetoapre -segmenteddocument. Theresultsofthisexperimentaregivenin lastrowofTable1,andtheyreflectonlyasmall overalldeclineinperformancefromthe Novemberresults. These scores reflectivery strongagreementandrepresentasignificant improvementoverpreviouslyreportedresultson annotating multipletext sinthe RST framework (Marcuetal., 1999).

Table2reportsfinalresultsforallpairsof taggerswhodouble -annotatedfourormore documents,representing30outofthe53 documentsthatweredouble -tagged.Resultsare basedonpre -segmenteddocuments.

Ourteamwasabletoreachasignificant levelofconsistency, eventhough they faced a numberofchallengeswhichreflectdifferences intheagreements coresatthe various levels. Whileoperatingundertheconstraintstypicalof anytheoreticalapproach inanapplied environment, the annotators faced at askin whichthecomplexityincreasedassupportfrom theguidelinestendedtodecrease. Thus, while rulesforsegmentingwerefairlyprecise, annotatorsreliedonheuristicsrequiringmore humanjudgment toassignrelationsand nuclearity. Another factor is that the cognitive challengeofthetaskincreasesasthetreetakes shape. It is relatively straightforward for the annotatortomakeadecisiononassignmentof nuclearityandrelationattheinter -clausallevel, butthisbecomesmorecomplexattheinter sententiallevel, and extremely difficult when linkinglargesegments.

Thistensionbetweentaskcomplexityand guidelineunder -specificationresultedfromthe practicalapplicationofatheoretical modelona broadscale. Whileotherdiscourse theoretical approachespositdistinctlydifferenttreatments forvariouslevelsofthediscourse(VanDijkand Kintsch, 1983; Meyer, 1985), RST relies on a standardmethodologytoanalyzethedocument atalll evels. The RST relation set is richard the conceptofnuclearity, somewhat interpretive. Thisgaveourannotatorsmoreleewayin interpretingthehigherlevelsofthediscourse structure, thus introducing some stylistic differences, which may prove an int eresting avenueoffutureresearch.

5 CorpusDetails

TheRSTCorpusconsistsof385WallStreet JournalarticlesfromthePennTreebank, representingover176,000wordsoftext.In ordertomeasureinter -annotatorconsistency,53 ofthedocuments(13.8%)we redouble -tagged. Thedocumentsrangeinsizefrom31to2124 words,withanaverageof458.14wordsper document.Thefinaltaggedcorpuscontains 21,789EDUswithanaverageof56.59EDUs perdocument.Theaveragenumberofwordsper EDUis8.1.

Thearti clesrangeoveravarietyoftopics, includingfinancialreports, generalinterest stories, business -relatednews, culturalreviews, editorials, and letters to the editor. In selecting these documents, we partnered with the Linguistic Data Consortium to se lect 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, and relateddocumentation and resources, see: http://www.isi.edu/~marcu/discourse.

6 Discussion

Agrowingnumberofgroupshavedevelopedor aredevelopingdiscourse -annotatedcorporafor text. These can be characterized b oth interms of the kinds of features annotated as well as by the scope of the annotation. Features may include specific discourse cuesor markers, core ference links, identification of the torical relations, etc. The scope of the annotation refers to the le vels of an alysis within the document, and can be characterized as follows:

- sentential:annotationoffeaturesatthe intra-sententialorinter -sententiallevel,ata singlelevelofdepth(Sundheim,1995; Tsouetal.,2000;NomotoandMatsumoto, 1999; Rebeyrolle,2000).
- hierarchical:annotationoffeaturesat multiplelevels,buildinguponlowerlevels ofanalysisattheclauseorsentencelevel (MoserandMoore,1995;Marcu,etal. 1999)
- document-level:broadcharacterization of documentstructuresuch asidentification of topicalsegments(Hearst,1997),linking of largetextsegmentsviaspecificrelations (Ferrari,1998;Rebeyrolle,2000),or definingtextobjectswithatextarchitecture (Pery-WoodleyandRebeyrolle,1998).

Developing corpora with hesekinds of rich annotationisalabor -intensiveeffort.Building theRSTCorpusinvolvedmorethanadozen peopleonafullorpart -timebasisoveraone yeartimeframe(Jan. -Dec.2000). Annotation ofasingledocumentcouldtakeanywherefrom 30min utestoseveralhours, depending on the lengthandtopic.Re -taggingofalargenumber ofdocumentsaftermajorenhancementstothe annotationguidelineswasalsotimeconsuming. Inaddition, limitations of the theoretical approachbecamemoreapparentove rtime. BecausetheRSTtheorydoesnotdifferentiate betweendifferentlevelsofthetreestructure.a fairlyfine -grainedsetofrelationsoperates between EDUs and EDU clusters at the macrolevel. The procedural knowledge available at the

EDUlevelisl ikelytoneedfurtherrefinement forhigher -leveltextspansalongthelinesof otherworkwhichpositsafewmacro -level relationsfortextsegments, such as Ferrari (1998)orMeyer(1985).Moreover,usingthe RSTapproach, the resultant treestructure, likea traditionaloutline, imposed constraints that otherdiscourserepresentations(e.g.,graph) wouldnot.Incombinationwiththetree structure, the concept of nuclearity also guided anannotatortocaptureoneofanumberof possiblestylisticinterp retations. Weourselves are eager to explore these aspects of the RST, andexpectnewinsightstoappearthrough analysisofthecorpus.

WeanticipatethattheRSTCorpuswillbe multifunctionalandsupportawiderangeof languageengineeringapplications .Theadded valueofmultiplelayersofovertlinguistic phenomenaenhancingthePennTreebank informationcanbeexploitedtoadvancethe studyofdiscourse,toenhancelanguage technologiessuchastextsummarization, machinetranslationorinformationr etrieval,or tobeatestbedfornewandcreativenatural languageprocessingtechniques.

References

BruceBrittonandJohnBlack.1985. *UnderstandingExpositoryText*. Hillsdale,NJ:
LawrenceErlbaumAssociates.

JillBurstein,DanielMarcu,SlavaAndreye vandMartinChodorow.2001.Towards automaticidentificationofdiscourseelementsin essays.In *Proceedingsofthe39* *** Annual MeetingoftheAssociationforComputational Linguistics, Toulouse,France.

JeanCarletta, AmyIsard, StephenIsard, JacquelineKowtko, Gwyneth Doherty - Sneddon, and Anne Anderson. 1997. The reliability of a dialogue structure coding scheme. Computational Linguistics 23(1):13 -32.

GiacomoFerrari.1998.Preliminarysteps towardthecreationofadiscourseandtext resource.In *ProceedingsoftheFirst InternationalConferenceonLanguage ResourcesandEvaluation(LREC1998)*, Granada.Spain.999 -1001.

GiovanniFlammiaandVictorZue.1995. Empiricalevaluationofhumanperformanceand agreementinparsingdiscourseconstituentsin spokendialogue.In Proceedingsofthe4 th EuropeanConferenceonSpeech CommunicationandTechnology, Madrid,Spain, vol.3,1965 -1968.

RogerGarside, SteveFligelstoneandSimon Botley. 1997. Discourse Annotation: Anaphoric Relations in Corpora. In Corpusannotation: Linguisticinformation from computer text corpora, edited by R. Garside, G. Leech, and T. McEnery. London: Longman, 66 -84.

TalmyGivon.1983.Topiccontinuityin discourse.In *TopicContinuityinDiscourse:a QuantitativeCross -LanguageStudy*. Amsterdam/Philadelphia:JohnBenjamins,1 -41. JosephEvansGrimes.1975 .*TheThreadof*

Discourse. The Hague, Paris: Mouton.
Barbara Groszand Candice Sidner. 1986.
Attentions, intentions, and the structure of discourse. Computational Linguistics, 12(3): 175-204.

MartiHearst.1997.TextTiling:Segmenting textintomulti -paragraphsubtopicpassages. *ComputationalLinguistics* 23(1):33 -64.

JuliaHirschbergandDianeLitman.1993. Empiricalstudiesonthedisambiguationofcue phrases. *ComputationalLinguist ics*19(3):501 - 530.

EduardHovy.1993.Automateddiscourse generationusingdiscoursestructurerelations. *ArtificialIntelligence* 63(1-2):341 -386.

KlausKrippendorff.1980. *ContentAnalysis: AnIntroductiontoitsMethodology*. Beverly Hills.CA:SagePub lications.

GeoffreyLeech, TonyMcEnery, and Martin Wynne. 1997. Further levels of annotation. In Corpus Annotation: Linguistic Information from Computer Text Corpora, edited by R. Garside, G. Leech, and T. McEnery. London: Longman, 85-101.

RobertLongacre .1983 .TheGrammarof Discourse.NewYork:PlenumPress.

WilliamMannandSandraThompson.1988. Rhetoricalstructuretheory.Towardafunctional theoryoftextorganization. *Text*,8(3):243 -281.

WilliamMannandSandraThompson,eds. 1992. DiscourseDesc ription:DiverseLinguistic AnalysesofaFund -raisingText. Amsterdam/Philadelphia:JohnBenjamins.

DanielMarcu.2000. The Theory and Practice of Discourse Parsing and Summarization. Cambridge, MA: The MIT Press.

Daniel Marcu, Estibaliz Amorrortu, and Magdelena Romera. 1999. Experiments in constructing a corpus of discourse trees. In *Proceedings of the ACL Workshop on Standards and Tools for Discourse Tagging*, College Park, MD. 48-57.

DanielMarcu,LynnCarlson,andMaki Watanabe.2000.Theautomatictran slationof discoursestructures. *ProceedingsoftheFirst AnnualMeetingoftheNorthAmericanChapter oftheAssociationforComputational Linguistics*,Seattle,WA,9 -17.

MitchellMarcus,BeatriceSantorini,and MaryAnnMarcinkiewicz.1993.Buildinga largeannotatedcorpusofEnglish:thePenn Treebank, *ComputationalLinguistics* 19(2), 313-330.

BonnieMeyer.1985.ProseAnalysis:
Purposes,Procedures,andProblems.In
UnderstandingExpositoryText ,editedbyB.
BrittonandJ.Black.Hillsdale,NJ:Lawren ce
ErlbaumAssociates,11 -64.

JohannaMoore.1995. Participatingin ExplanatoryDialogues:Interpretingand RespondingtoQuestionsinContext.

Cambridge,MA:MITPress.

JohannaMooreandCecileParis.1993. Planningtextforadvisorydialogues:capturing intentionalandrhetoricalinformation. *ComputationalLinguistics* 19(4):651 -694.

MeganMoserandJohannaMoore.1995.
Investigatingcueselectionandplacementin tutorialdiscourse. *Proceedingsofthe33 AnnualMeetingoftheAssociationfor ComputationalLinguistics*, Cambridge,MA, 130-135.

TadashiNomotoandYujiMatsumoto.1999. Learningdiscourserelationswithactivedata selection.In *Proceedingsofthe JointSIGDAT ConferenceonEmpiricalMethodsinNatural LanguageProcessingandVeryLargeCorp ora*, CollegePark,MD,158 -167.

RebeccaPassonneauandDianeLitman. 1997.Discoursesegmentationbyhumanand automaticmeans. *ComputationalLinguistics* 23(1):103 -140.

Marie-PaulePery -WoodleyandJosette Rebeyrolle.1998.Domainandgenrein sublanguagetext:definitionalmicrotextsin threecorpora.In *ProceedingsoftheFirst InternationalConferenceonLanguage ResourcesandEvaluation(LREC* -1998), Granada,Spain,987 -992. LiviaPolanyi.1988.Aformalmodelofthe structureofdiscourse. *Journalof Pragmatics* 12:601 -638.

LiviaPolanyi.1996.Thelinguisticstructure of discourse.CenterfortheStudyofLanguage andInformation.CSLI -96-200.

JosetteRebeyrolle.2000.Utilisationde contextesdéfinitoirespourl'acquisitionde connaissancesàpartir detextes.In *Actes JournéesFrancophonesd'Ingénieriedela Connaissance(IC'2000)*, Toulouse,IRIT,105 - 114.

HarveySacks, Emmanuel Schegloff, and Gail Jefferson. 1974. A simple systematics for the organization of turntaking inconversation. *Language* 50: 696-735.

SidneySiegalandN.J.Castellan.1988. *NonparametricStatisticsfortheBehavioral Sciences*.NewYork:McGraw -Hill.

BethSundheim.1995.Overviewofresultsof the MUC - 6 evaluation. In *Proceedings of the Sixth Message Understanding Conference* (MUC-6), Columbia, MD, 13-31.

BenjaminK.T'sou,TomB.Y.Lai,Samuel W.K.Chan,WeijunGao,andXuegangZhan. 2000.EnhancementofChinesediscourse markertaggerwithC.4.5.In *Proceedingsofthe SecondChineseLanguageProcessing Workshop*, HongKong,38 -45.

TeunA. Van Dijkand Walter Kintsch. 1983. Strategies of Discourse Comprehension. New York: Academic Press.

EllenVoorheesandDonnaHarman.1999. TheEighthTextRetrievalConference(TREC 8).NISTSpecialPublication500 -246.

CharlesWayne.2000.Mult ilingualtopic detectionandtracking:successfulresearch enabledbycorporaandevaluation.In ProceedingsoftheSecondInternational ConferenceonLanguageResourcesand Evaluation(LREC -2000),Athens,Greece, 1487-1493.

JanyceWiebe,RebeccaBruce, andThomas O'Hara.1999.Developmentanduseofagold standarddatasetforsubjectivityclassifications. In *Proceedingsofthe37* thAnnualMeetingofthe AssociationforComputationalLinguistics. CollegePark,MD,246 -253.