SciDTB: Discourse Dependency Treebank for Scientific Abstracts



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Outline

- Background: discourse dependency structure & treebanks
- Main work: details about SciDTB
 - Annotation framework
 - Corpus construction
 - Statistical analysis
 - SciDTB as evaluation benchmark
- Conclusion & summary

Discourse Dependency Structure & Treebanks

Example text: [Syntactic parsing is useful in NLP.]_{e1} [We present a parsing algorithm,]_{e2} [which improves classical transition-based approach.]_{e3}



Discourse dependency treebanks:

- Conversion based dependency treebanks from RST or SDRT representations [Li. 2014; Stede. 2016]
- Limitations: conversion errors and not support non-projection
- Build a dependency treebank from scratch
- Scientific abstracts: short with strong logics

Annotation Framework: Discourse Segmentation

Discourse segmentation: Segment abstracts into elementary discourse units (EDUs)

Guidelines:

- Generally treats clauses as EDUs [Polanyi. 1988, Mann and Thompson. 1988]
- Subjective and some objective clauses are not segmented [Carlson and Marcu. 2001]

Example 1: [The challenge of copying mechanism in Seq2Seq is that new machinery is needed]_{e1} [to decide when to perform the operation.]_{e2}

• Strong **discourse cues** always starts a new EDU

Example 2: [Despite bilingual embedding's success,]_{e1} [the contextual information]_{e2} [which is important to translation quality,]_{e3} [was ignored in previous work.]_{e4}

Annotation Framework: Obtain Tree Structure

- A tree is composed of relations $\langle e_h, r, e_d \rangle$
 - e_h : the EDU with essential information
 - e_d : the EDU with supportive content
 - r: relation type (17 coarse-grained and 26 fine-grained types)
- Each EDU has one and only one head
 - One EDU is dominated by ROOT node
- Polynary relations

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Multi-coordination



One-dominates-many

Annotation Example in SciDTB

ROOT There is rich knowledge Goal encoded in online web data. Addition $\rightarrow e_2$ For example, entity tags in Wikipedia data define some word boundaries. Example $\rightarrow e_3$ ROOT In this paper we adopt partial-label learning with conditional random fields e_4 to make use of this knowledge for semi-supervised Chinese word segmentation. Enablement $\rightarrow e_5$ The basic idea of partial-label learning is to optimize a cost function Aspect $\rightarrow e_6$ that marginalizes the probability mass in the constrained space Addition $\rightarrow e_7$ that encodes this knowledge. Addition $\rightarrow e_8$ By integrating some domain adaptation techniques, such as EasyAdapt, Manner means $\rightarrow e_9$ Evaluation our result reaches an F-measure of 95.98 % on the CTB-6 corpus. e_{10}

Abstract from http://www.aclweb.org/anthology/

Corpus Construction

- Annotator Recruitment:
 - 5 annotators were selected after test annotation
- EDU Segmentation:
 - Semi-automatic: pre-trained SPADE [Soricut. 2003] + Manual proofreading

• Tree Annotation:

- The annotation lasted 6 months
- 63% abstracts were annotated more than twice
- An online tool was developed for annotating and visualizing DT trees

Online Annotation Tool



Website: http://123.56.88.210/demo/depannotate/

Reliability: Annotation Consistency

- The consistency of tree annotation is analyzed by 3 metrics:
 - Unlabeled accuracy score: structural consistency
 - Labeled accuracy score: overall consistency
 - Cohen's Kappa: consistency on relation label conditioned on same structure

Annotators	#Doc.	UAS	LAS	Kappa score
Annotator 1 & 2	93	0.811	0.644	0.763
Annotator 1 & 3	147	0.800	0.628	0.761
Annotator 1 & 4	42	0.772	0.609	0.767
Annotator 3 & 4	46	0.806	0.639	0.772
Annotator 4 & 5	44	0.753	0.550	0.699

Annotation Scale

- SciDTB is
 - comparable with PDTB and RST-DT considering size of units and relations
 - much larger than existing domain-specific discourse treebanks

Corpus	#Doc.	#Doc. (unique)	#Text unit	#Relation	Source	Annotation form
SciDTB	1355	798	18978	18978	Scientific abstracts	Dependency trees
RST-DT	438	385	24828	23611	Wall Street Journal	RST trees
PDTB v2.0	2159	2159	38994	40600	Wall Street Journal	Relation pairs
BioDRB	24	24	5097	5859	Biomedical articles	Relation pairs

Structural Characteristics

- Dependency distance
 - Most relations (61.6%) occur between neighboring EDUs
 - The distance of 8.8% relations is greater than 5



• Non-projection: 3% of the whole corpus

SciDTB as Benchmark

- We make SciDTB as a benchmark for evaluating discourse dependency parsers
- Data partition: 492/154/152 abstracts for train/dev/test set
- 3 baselines are implemented:
 - Vanilla transition based parser
 - Two-stage transition based parser a simpler version of [Wang, 2017]
 - Graph based parser

Model	Dev	/ set	Test set		
	UAS	LAS	UAS	LAS	
Vanilla transition	0.730	0.557	0.702	0.535	
Two-stage transition	0.730	0.577	0.702	0.545	
Graph-based	0.577	0.455	0.576	0.425	
Human	0.806	0.627	0.802	0.622	

Conclusions

- Summary:
 - We propose a discourse dependency treebank with following features:
 - constructed from scratch
 - Scientific abstracts
 - comparable with existing treebanks in size
 - We further make SciDTB as a benchmark
- Future work:
 - Consider longer scientific articles
 - Develop effective parsers on SciDTB

Thank you!

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SciDTB is available: https://github.com/PKU-TANGENT/SciDTB