Joint Syntacto-Discourse Parsing and the Syntacto-Discourse Treebank

Motivations

Most discourse parsers are pipelined (rather than end-toend), sophisticated, not self-contained:

- they assume gold segmentations (EDUs);
- they use external parsers for syntactic features.

Here we propose:

- Syntacto-Discourse Treebank: a combined representation of the constituency and discourse trees
- facilitates parsing at both levels w/o explicit conversion
- a joint treebank based on Penn Treebank and RST Treebank
- the first **end-to-end** discourse parser
- jointly parses at constituency and discourse levels.
- do not use any explicit syntactic features.
- no need to do binarization.

Combined Representation & Treebank

RST Discourse Tree (Fig. 1 (a))

- Elementary Discourse Units (EDUs) as leaf nodes
- mostly binary branching
- *nucleus* (•): core semantic meaning of the branching
- *satellite* (°): semantically decorating nucleus
- *relations*: e.g., "Purpose", "Background"
- multi-branching for conjunctions
- e.g., "List", "Comparison"

Combined Representation

- low-level lexical and syntactic info greatly help determining EDUs, structures, and relations.
- previously from pre-trained tools
- we directly determine the segmentations, syntactic trees, and discourse parses w/ a single joint parser. trained on combined trees of constituency and discourse.

Step 1: Convert RST tree to constituency tree format

 binary branching: use relation + nucleus/satellite direction as label of the parent

Elaboration ← Elaboration • • • to • • • • • •

• multi-branching: use the relation as the label

Step 2: Replace the leaf EDUs with syntactic (sub)trees

- in most cases, one EDU aligns to one single (sub)tree
- when one EDU corresponds to multiple (sub)trees, we take the lowest common ancestor as parent node

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• alternate between structural (sh, comb) and label (label_X, nolabel) actions

• after structural actions, keep branching point k,

• k will be used later in determing the relations b/w EDUs

• k disappears after label action

nolabel makes binarization of the

discourse/constituency tree unnecessary





Deductive System

$$w_{0} \dots w_{n-1}$$

$$\langle -1 \bigtriangleup 0 \rangle : (0, \emptyset) \quad \text{goal} \quad \langle -1 \bigtriangleup 0 \bigtriangleup n \rangle : (_, t)$$

$$\frac{\langle \dots i \bigtriangleup j \rangle : (c, t)}{\langle \dots i \bigtriangleup j \swarrow j + 1 \rangle : (c + sc_{\text{sh}}(i, j), t)} \quad j < n$$

$$\langle \dots i \bigtriangleup k \bigtriangleup j \rangle : (c, t)$$

$$\langle \dots i \bigtriangleup k \leftthreetimes j \rangle : (c + sc_{\text{comb}}(i, k, j), t)$$

$$\langle \dots i \bigtriangleup k \leftthreetimes j \rangle : (c, t)$$

$$\langle \dots i \bigtriangleup j \rangle : (c + sc_{\text{label}_{X}}(i, k, j), t \cup \{iX_{j}\})$$

$$\langle \dots i \bigtriangleup j \rangle : (c + sc_{\text{nolabel}}(i, k, j), t)$$

Recurrent Neural Models

 bi-directional LSTM in Cross & Huang (2016) no explicit discourse/syntactic tree structures represented in features

span boundaries LSTM representations are passed to FF network to calc. likelihoods of actions/labels

Training & Emiprical Evaluation

• use "training with exploration" & dynamic oracle

 set most hyperparams based on Cross & Huang 2016 • use higher β (= 0.8) to discourage exploration • lower β leads to more diversions to wrong trajectories for larger discourse trees

End-to-End Comparison (F1 scores)

	description	synt. feats	seg.	struct.	+nuc.	+rel.
	segment. only	Stanford	95.1	-	-	-
)	end-to-end pipe.	PTB	94.0	72.3	59.1	47.3
-discourse parsing		-	95.4	78.8	65.0	52.2

Comparison w/ Gold Segmentation (F1 scores)

	syntactic feats		struct.	+nuc.	+rel.
human annotation -		-	88.7	77.7	65.8
	Hernault et al. 2010	Penn Treebank	83.0	68.4	54.8
e	Joty et al. 2013	Charniak (retrained)	82.7	68.4	55.7
spars	Joty + Moschitti 2014	Charniak (retrained)	-	-	57.3
	Feng & Hirst 2014	Stanford	85.7	71.0	58.2
	Heilman + Sagae 2015	ZPar (retraied)	83.5	68.1	55.1
	Wang et al. 2017	Stanford	86.0	72.4	59.7
al	Li et al. 2014	Stanford	82.4	69.2	56.8
neura	+ sparse features	Stanioru	84.0	70.8	58.6
	Ji & Eisenstein 2014	ΝΛΑΙΤ	80.5	68.6	58.3
	+ sparse features		81.6	71.1	61.8
span-based disc. parsing		-	84.2	67.7	56.0