Neural Discourse Structure for Text Categorization

Yangfeng Ji and Noah Smith

Presented by Ji Li

Ji, Yangfeng, and Noah Smith. "Neural discourse structure for text categorization." arXiv preprint arXiv: 1702.01829 (2017).

Outline

- Motivation
- Background
- Model
- Experiment results
- Discussion and conclusion

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Text Categorization

- Important for applications like sentiment analysis, inferring authorship and making predictions
- How to represent text?
  - Bag of words
  - Representation learning

- How does different part of text contribute to the representation?
  - Different part of text may influence the text category in different weight

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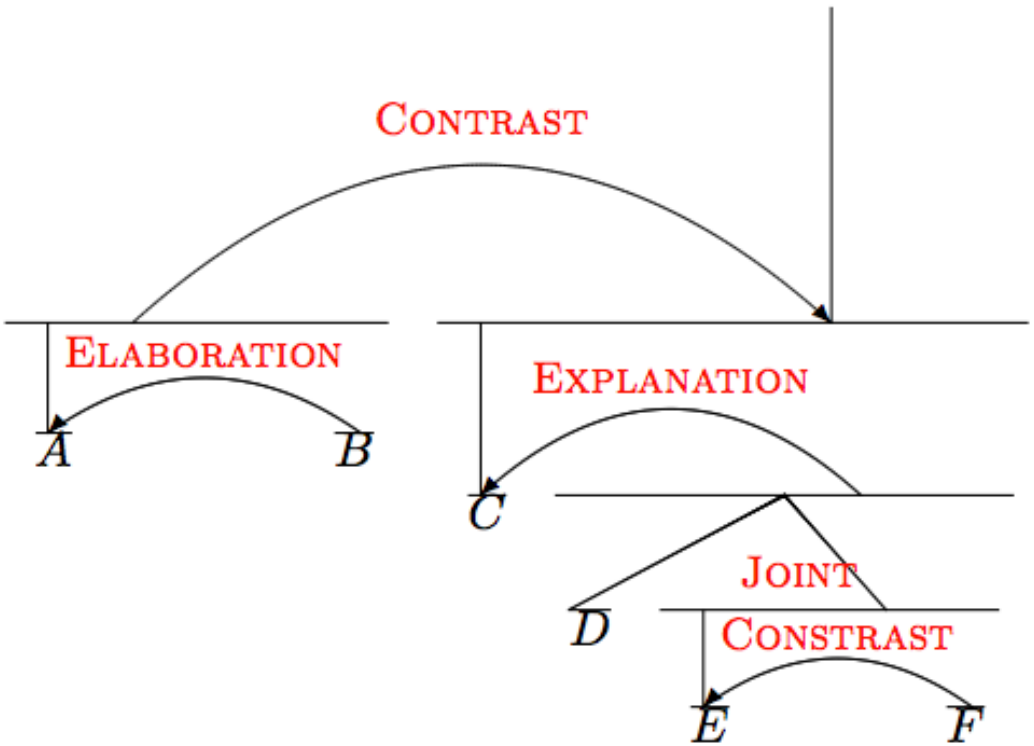
Rhetorical Structure Theory



[Although the food was amazing]^{A} [and I was in love with the spicy pork burrito,]^{B} [the service was really awful.]^{C} [We watched our waiter serve himself many drinks.]^{D} [He kept running into the bathroom]^{E} [instead of grabbing our bill.]^{F}

Document can be represented by a tree.

Elementary Discourse Unit (EDU), connected via discourse relations.

Discourse Parsing from Linear Projection

- Shift reduced discourse parsing
  - Maintain a stack and a queue
  - Consider features of 3 EDUs, *v = [v1; v2; v3]*

- Formulate the decision as a multi-class shift-reduce classifier

$$\hat{m} = \underset{m \in \{1,\ldots,C\}}{\arg\max}\ \mathbf{w}_m^\top \mathbf{f}(\mathbf{v}; \mathbf{A})$$

Ji, Yangfeng, and Jacob Eisenstein. "Representation learning for text-level discourse parsing." Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). Vol. 1. 2014.

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Model

- Recursive neural network build on discourse dependency tree
- Distributed representation of EDU achieved with bidirectional LSTM
- Let *vi* denote the vector representation of EDU *i* and its descendants
  - If *vi* is leaf: *vi = tanh(ei)*
  - Other wise:

$$\mathbf{v}_i = \tanh\left(\mathbf{e}_i + \sum_{j \in children(i)} \alpha_{i,j} \mathbf{W}_{r_{i,j}} \mathbf{v}_j\right)$$

$$\alpha_{i,j} = \sigma\left(\mathbf{e}_i^\top \mathbf{W}_\alpha \mathbf{v}_j\right)$$

Model ablations and baselines

- Unlabeled Model

$$\mathbf{v}_i = \tanh\left(\mathbf{e}_i + \sum_{j \in children(i)} \alpha_{i,j}\mathbf{v}_j\right)$$

- Root
  - Use discourse structure to select the root and use only the root EDU representation
- Additive
  - Use all EDUs with simple average

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Performance

Method	Yelp	MFC	Debates	Movies	Bills
Prior work					
1. Yang et al. (2016)	71.0	—	—	—	—
2. Card et al. (2016)	—	56.8	—	—	—
3. Yogatama and Smith (2014)	—	—	74.0	—	88.5
4. Bhatia et al. (2015)	—	—	—	82.9	—
5. Hogenboom et al. (2015)	—	—	—	71.9	—
Variants of our model					
6. ADDITIVE	68.5	**57.6**	69.0	82.7	80.1
7. ROOT	54.3	51.2	60.3	68.7	70.5
8. UNLABELED	**71.3**	**58.4**	**75.7**	**83.1**	78.4
9. FULL	**71.8**	56.3	**74.2**	79.5	77.0

Table 2: Test-set accuracy across five datasets. Results from prior work are reprinted from the corresponding publications. Boldface marks performance stronger than the previous state of the art.

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Case Study

From DPLP:

$$2C \xrightarrow[\text{EVALUATION}]{0.70} 2B \xrightarrow[\text{EVALUATION}]{0.87} 2A \xleftarrow[\text{ELABORATION}]{0.61} 2D$$

[I love these people.]^{2A} [They are very friendly and always ask about my life.]^{2B} [They remember things I tell them then ask about it the next time I'm in.]^{2C} [Patrick and Lily are the best but everyone there is wonderful in their own ways.]^{2D}

(b) true label: 5, predicted label: 5

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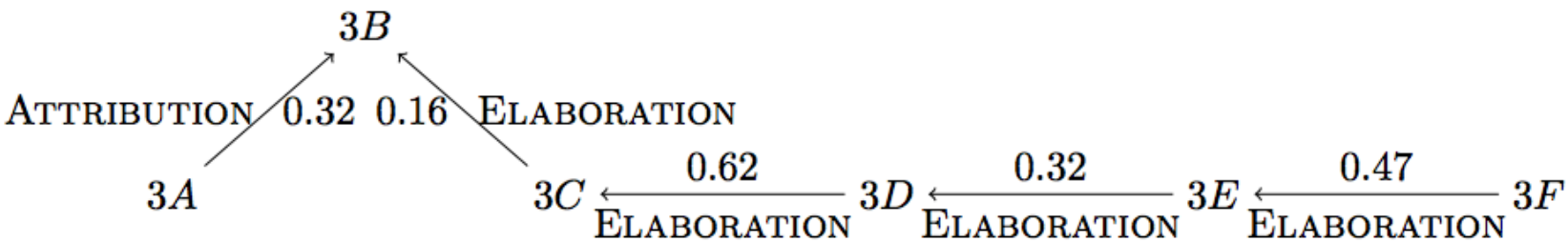
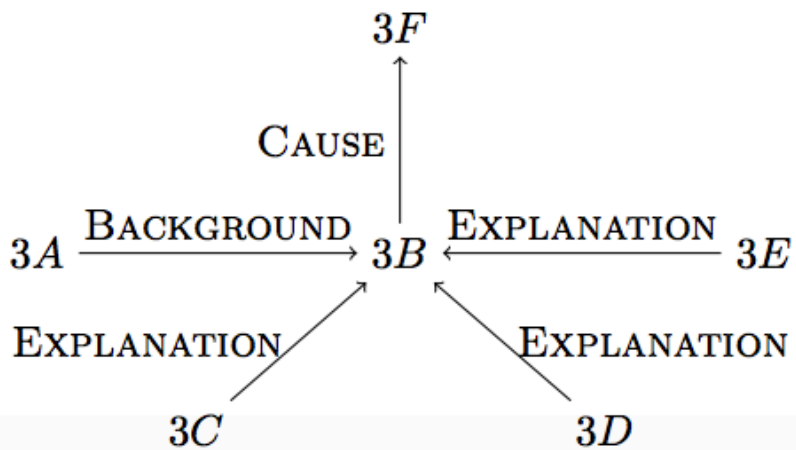
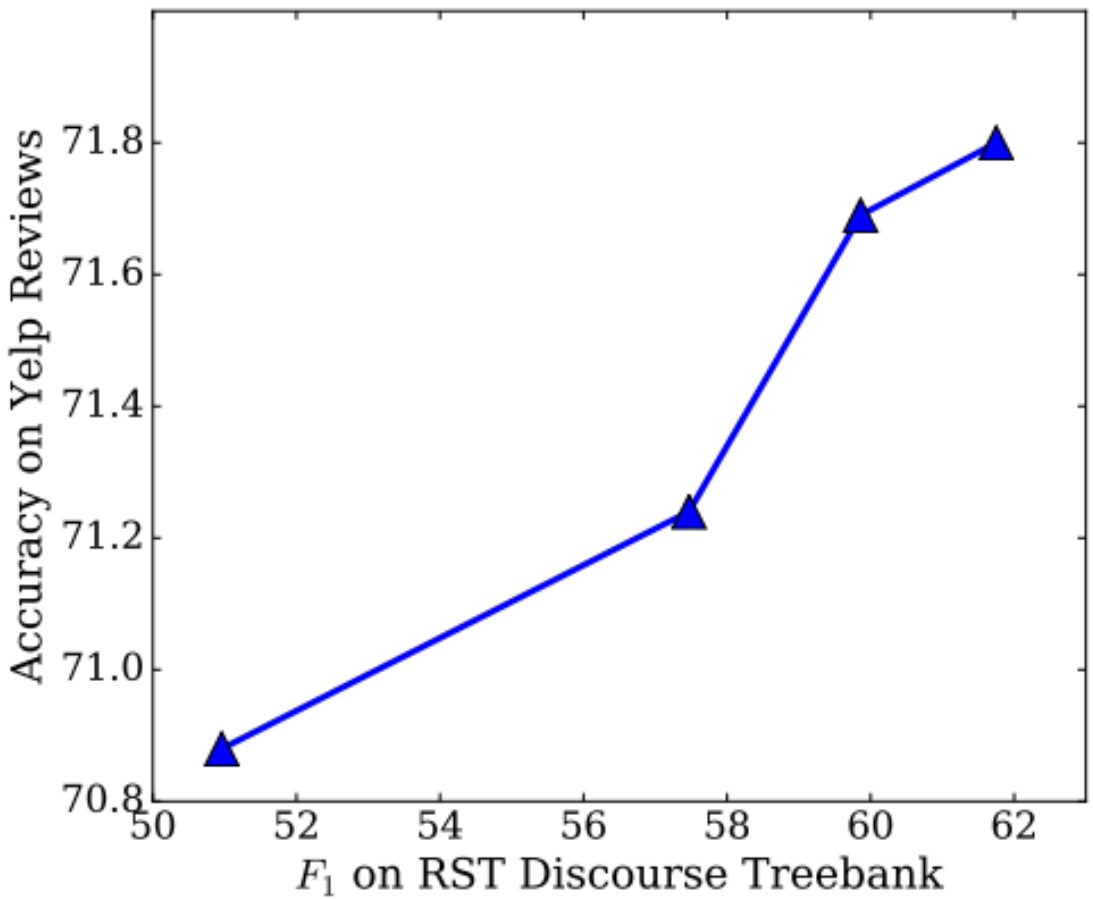


Manually constructed:



[We use to visit this pub 10 years ago because they had a nice english waitress and excellent fish and chips for the price.]^{3A} [However we went back a few weeks ago and were disappointed.]^{3B} [The price of the fish and chip dinner went up and they cut the portion in half.]^{3C} [No one assisted us in putting two tables together we had to do it ourselves.]^{3D} [Two guests wanted a good English hot tea and they didn't brew it in advance.]^{3E} [So we've decided there are newer and better places to eat fish and chips especially up in north phoenix.]^{3F}

Other experiment



Further improvement on Discourse structure can potentially enhance performance.

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Discussion and Conclusion

- Automatically-derived discourse structure can be helpful to text categorization.

- Two major limitations:
  - Performance of discourse parser.
  - Domain mismatch between training corpus and future test data.

- Motivates further improvement of discourse parser and exploration of domain adaptation methods.

Thank you