AAAI 19 rebuttal

We thank all the reviewers for their detailed and helpful feedback.

Reviewer #1

- What tweaks does your Combined model need in order to be used on other relation extraction applications, where the existence of a relation is sparse?

  Our model can be used on other relation extraction tasks. While the results are empirical, there are two things to note. First, our model is at the document level (in contrast, most existing work on relation extraction system is at the sentence level). Second, our Combined model integrates entity prior information, which is absent in most relation extraction models. Integrating such information, entities involved in a new relation extraction task can be embedded using external knowledge such as KB.

- In rule-based model, when assigning blame direction between two entities, why did you use aggressiveness scores deterministically instead of probabilistically?

  We measure the aggressiveness score for a simple yet intuitive baseline, which is devised to measure the inclination of some entity blaming others or being blamed. While we have not tried a probabilistic rule-based model, our entity prior baseline is probabilistic, in which entity embeddings entail aggressiveness information implicitly.

- How do you predict your Context model would work on articles translated from a foreign language into English? Do you think this could be another domain where the Combined model would do way better?

  The performance of the Context model on translated articles should depend on the translation style -- our model is trained on NYT/WSJ/USA Today data, and thus English written in similar genre should be affected the least. In contrast, machine translated text might suffer larger loss.

  The Combined model uses entity prior information, which is invariant during translation. Thus, there is reason to expect that the Combined model would do much better in this case.

Reviewer #2

- Why does the problem need another “from scratch” approach and implementation and why is there no attempt to adapt existing methods and implementations for related problems?

  This is a nice point and we will make more relevant discussions. Our work differs from existing work on relation extraction in two main aspects. First, our work is at the document level, while most existing work on relation extraction focuses on the sentence level (there has been a few papers working on passage level relation extraction, but our goal is to extract blame ties from whole news articles). Second, our work explicitly uses entity prior information on blame patterns, which does not make sense in general domain relation extraction. Most existing work mixes entity and content information in modeling relations.

With regard to the structure of the Context model, our work is similar in structure to some existing work indeed, such as Nguyen and Grishman (2015), who used CNN and max pooling. We use BiLSTM and max pooling for encoding. We will add such discussions in Related Work.

Reviewer #3

- Have you considered the use of semantics to detect the blame actors?

  We use a BiLSTM model to encode the text, which may learn the implicit semantic information.

- The manual annotation process is not clearly described. Is it performed by linguists?

  It is performed by a social science professor and validated by two graduate students working in the NLP field.

- It is good that there is an attempt on generalization, however, an accuracy of 8/13 articles is not very significant. Could you provide us with more statistics/information about the articles that you have used in the generalization?

  We used Google News as the data source. We manually checked news in January 2018 and picked 13 articles which involve blame. The news articles are from various sources such as CNN, BBC News, Wall Street Journal and Washington Post. The time span is quite different from the financial crisis dataset (2007-2010). We will add more discussions in the article.