View Reviews

Paper ID
2972

Paper Title
Who Blames Whom in a Crisis? Detecting Blame Ties from News Articles Using Neural Networks

Reviewer #1

Questions

1. [Summary] Please summarize the main claims/contributions of the paper in your own words.
This paper proposes a model that extracts Blame relations from text. In so doing, the paper creates two neural network models: Entity model, that learns relations between entities, and Context model that leverages linguistic structure. Then it proposes Combined model, which combines the two. The paper evaluates the performance of the three models, and shows generalizability of models to new cases.

2. [Relevance] Is this paper relevant to an AI audience?
Likely to be of interest to a large proportion of the community

3. [Significance] Are the results significant?
Significant

4. [Novelty] Are the problems or approaches novel?
Novel

5. [Soundness] Is the paper technically sound?
Technically sound

6. [Evaluation] Are claims well-supported by theoretical analysis or experimental results?
Very convincing

7. [Clarity] Is the paper well-organized and clearly written?
Excellent

8. [Detailed Comments] Please elaborate on your assessments and provide constructive feedback.
This is a very good paper. The main question of blame attribution is highly important, and it is not a trivial task to extract blame relations from text. The models are novel and generalizable to other applications. The authors provided a sufficient evaluation for their models. The paper is also easy to read.

9. [QUESTIONS FOR THE AUTHORS] Please provide questions for authors to address during the author feedback period.
- 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?
- In rule based model, when assigning blame direction between two entities, why did you use aggressiveness scores deterministically instead of probabilistically?
- 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?

10. [OVERALL SCORE]
8 - Accept (Top 50% accepted papers (est.))

11. [CONFIDENCE]
Reviewer is knowledgeable in the area

Reviewer #3

Questions

1. [Summary] Please summarize the main claims/contributions of the paper in your own words.

The paper studies the problem of extracting blame ties in news articles, i.e. occurrences in the text where A blames B. They hand-annotate a training corpus of articles related to the financial crisis in published in the NYT, WSJ and USA Today for triples of blame source, blame target and "causality link". They experiment with different models including a rule-based model (combining distance from blame-keyword with "aggressiveness" for blame direction), an entity prior model, and a context model using LSTMs for word/entity embedding. The evaluation includes both previously seen entities (KNOWN) and unseen entities (ALL). The combined, entity+context model performs best in terms of generalization error (ALL, test set F1). The models and implementation will be released, as well as an online demo.

2. [Relevance] Is this paper relevant to an AI audience?

Relevant to researchers in subareas only

3. [Significance] Are the results significant?

Moderately significant

4. [Novelty] Are the problems or approaches novel?

Somewhat novel or somewhat incremental

5. [Soundness] Is the paper technically sound?

Technically sound

6. [Evaluation] Are claims well-supported by theoretical analysis or experimental results?

Sufficient

7. [Clarity] Is the paper well-organized and clearly written?

Good

8. [Detailed Comments] Please elaborate on your assessments and provide constructive feedback.

By and large this a decent paper with a fairly novel problem, a standard approach and a reasonable evaluation. The fact that code (and training data?) will be shared is a plus. Some additional related work could be discussed (see below) and some minor things could be improved.

Maybe explore a weakly supervised setting where only articles with titles of the form "X blames Y for Z" are used and the corresponding full text is then assumed to talk about entity X blaming entity Y for Z. This might allow automatically collecting a much larger data set. E.g. one could iterate across the main entities and then query Google News. Here are results for "trump blames …": https://news.google.com/search?q="trump+blames"

This shows that entities information alone may be useful in extracting blame ties than using contexts. (missing "more")

Once we have obtain representations -> obtained

Avoid reporting accuracies with three decimal digits when it's computed over 100 articles. E.g. there's an F1 score for the two annotators reported as 94.425%. Just 94% would be more appropriate and scientific.

Clarify if "sentence distance" refers to the number of sentences in between (starting at 0? Or 1?) or to the number of words.

The term "causality link" needs more explanation. This seems to be the "what", i.e. A blames B for X.

Related work:

Aspect of Blame in Tweets: A Deep Recurrent Neural Network Approach
https://dl.acm.org/citation.cfm?id=3051157

Twitter as an information dissemination tool has proved to be instrumental in generating user curated content in short spans of time. Tweeting usually occurs when reacting to events, speeches, about a service or product. This in some cases comes with its fair share of blame on varied aspects in reference to say an event. Our work in progress details how we plan to collect the informal texts, clean them and extract features for blame detection. We are interested in augmenting Recurrent Neural Networks (RNN) with self-developed association rules in getting the most out of the data for training and evaluation. We aim to test the performance of our approach using human-induced terror-related tweets corpus. It is possible tailoring the model to fit natural disaster scenarios.

Detecting Expressions of Blame or Praise in Text
http://www.lrec-conf.org/proceedings/lrec2016/summaries/942.html

The growth of social networking platforms has drawn a lot of attentions to the need for social computing. Social computing utilises human insights for computational tasks as well as design of systems that support social behaviours and interactions. One of the key aspects of social computing is the ability to attribute responsibility such as blame or praise to social events. This ability helps an intelligent entity account and understand other intelligent entities' social behaviours, and enriches both the social functionalities and cognitive aspects of intelligent agents. In this paper, we present an approach with a model for blame and praise detection in text. We build our model based on various theories of blame and include in our model features used by humans determining judgment such as moral agent causality, foreknowledge, intentionality and coercion. An annotated corpus has been created for the task of blame and praise detection from text. The experimental results show that while our model gives similar results compared to supervised classifiers on classifying text as blame, praise or others, it outperforms supervised classifiers on more finer-grained classification of determining the direction of blame and praise, i.e., self-blame, blame-others, self-praise or praise-others, despite not using labelled training data.

Conceptually, work looking at opinion extraction and opinion targets should also be related and could be used as a baseline.

Extracting opinions, opinion holders, and topics expressed in online news media text
https://dl.acm.org/citation.cfm?id=1654642

This paper presents a method for identifying an opinion with its holder and topic, given a sentence from online news media texts. We introduce an approach of exploiting the semantic structure of a sentence, anchored to an opinion bearing verb or adjective. This method uses semantic role labeling as an intermediate step to label an opinion holder and topic using data from FrameNet. We decompose our task into three phases: identifying an opinion-bearing word, labeling semantic roles related to the word in the sentence, and then finding the holder and the topic of the opinion word among the labeled semantic roles. For a broader coverage, we also employ a clustering technique to predict the most probable frame for a word which is not defined in FrameNet. Our experimental results show that our system performs significantly better than the baseline.

Joint extraction of entities and relations for opinion recognition
https://dl.acm.org/citation.cfm?id=1610136

Mentions “SOURCE blamed TARGET” in passing.

9. [QUESTIONS FOR THE AUTHORS] Please provide questions for authors to address during the author feedback period.

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?

10. [OVERALL SCORE]

6 - Marginally above threshold

11. [CONFIDENCE]

Reviewer is knowledgeable but out of the area

Reviewer #5

Questions

1. [Summary] Please summarize the main claims/contributions of the paper in your own words.
The authors propose neural net based models to detect blame ties (who blames who/what) in finance news articles. They approach the problem by building a dataset composed of finance news articles written to audiences of different social and political backgrounds and attempt to tackle challenges such as context, the complexity of sentences and irony by proposing NN models that also integrate entity and linguistic knowledge.

2. [Relevance] Is this paper relevant to an AI audience?
Relevant to researchers in subareas only

3. [Significance] Are the results significant?
Moderately significant

4. [Novelty] Are the problems or approaches novel?
Novel

5. [Soundness] Is the paper technically sound?
Technically sound

6. [Evaluation] Are claims well-supported by theoretical analysis or experimental results?
Sufficient

7. [Clarity] Is the paper well-organized and clearly written?
Good

8. [Detailed Comments] Please elaborate on your assessments and provide constructive feedback.
The related work section is somewhat weak. This section would gain a lot if you could contrast your work to some others that are performed as relation extraction tasks.
Since your main claim is the definition of a new task, it would be better if you could to emphasize how your work is more difficult than an ordinary event detection task or another one that is additionally related to discourse. It would help us understand your motivation better and the reason why you have specifically chosen the linguistic features that you went with rather than others.
In the related work section, the bibliography style in the first paragraph is inconsistent with the rest of the paper's (e.g Bamman and Smith [2015] instead of (Bamman and Smith 2015)).
On page 3, You should change the notation of the distance function since you have already named the news article "d", the name of the distance function should be something else.
The paper is easy to follow and the mathematical model is understandable. However, there are typos such as successfully extraction instead of extract on page 2, terns instead of terms on page 3, we have obtain instead of have obtained and has proved instead of has been proved on page 5.

9. [QUESTIONS FOR THE AUTHORS] Please provide questions for authors to address during the author feedback period.
Have you considered the use of semantics to detect the blame actors?
The manual annotation process is not clearly described. Is it performed by linguists?
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?

10. [OVERALL SCORE]
7 - Accept

11. [CONFIDENCE]
Reviewer is knowledgeable but out of the area