Designing a Crowdsourcing Tool to Measure Perceived Causal Relationships Between Narrative Events

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Abstract. The computational study of narrative is important to multiple academic disciplines. However, prior research has been limited by the inability to quantify subjects' comprehension of the causal structure within each narrative text. With the aid of big data technology and crowdsourcing tools, we aim to design a new approach to analysis the content of narratives in a data-driven manner, while also making these analyses scientifically replicable. The goal of this research is therefore to develop a tool that can be used to measure people's understanding of the causal relationships within a piece of text.

Keywords: Crowdsourcing · Narrative · Network · Rumor

1 Introduction

Narratives that transmit rumors underlie many important situations including: product/brand reputation, stock market oscillations, social unrest, and political decision-making [12,13]. Therefore, the study of these narratives is uniquely important to various groups including, but not limited to, public health officials, public relation professionals, market analysts and policy makers. In offline settings, rumor usually follows word of mouth patterns of dissemination [14, 19]. Nevertheless, the spread of information online has accelerated the spread of misinformation with negative implications for public understanding of science and public health [11]. The emergence of social media thus provides a platform for narrative rumor spread. Recent researches have shown that online communications enhance the word-of-mouth effects found offline [5,18]. As a result, rumors reach more people simultaneously and the effects of rumors last longer.

Many studies had done extensive work to explain the various mechanisms by which information is spread [2,10, 23, 26]. Most prior work has focused on describing the mechanism by which information is spread, and the external variables affecting this spread. Less work has analyzed how the content of a narrative affects its spread.

For example, fuzzy-trace theory, a leading theory of decision under risk, predicts that coherent narratives (those that present a clear gist explaining the causal relationship between events) are more likely to be accepted and shared by the public, even if the underlying facts may not be correct (as in the spread of misconceptions about the dangers associated with vaccination) [22]. This motivates the development of a technique that may be used to assess the relationship between the structure, coherence, and popularity of narrative rumors online.

Partially inherited from [14], in this study we define rumor as "unverified text-based information circulating on the internet". We focus on one key internal feature: a rumor narrative's causal structure, since prior work has shown that causal structure is a key component of narrative comprehension [24,25]. Each reader may comprehend the same piece of text differently. Therefore, the causal structure generated by individual reader is a direct lens through which we can measure their perception of the internal logic within a text. Furthermore, the extracted causal structure could provide a data source that can be used in other studies of information diffusion.

The goal of this project is to develop a tool that can conveniently collect readers' perceptions of a narrative's causal structure. We therefore propose a systematic approach to measuring these perceived causal structures.

2 Method

2.1 Representing Online Text as Causal Networks

Prior studies of narrative have concluded that causal networks are a replicable way to represent how humans understand text [15,24,25]. When describing a narrative as a causal network, each event in the narrative is represented by a node, whereas each causal relationship between events is represented as a link [25]. A simplified rule to determine whether a causal link exists from Event A to Event B is to determine "if A did not occur, then B would not have occurred" [24], based on the context of events A and B. Table 1 shows an example of labeled events in a simple narrative while Fig. 1 shows the associated causal networks.

Table 1. Labeled events in a simple narrative

Event Index	Text
1	Daniel arrived in his aunt's house.
2	He knocked at the door and
3	rang the doorbell
4	Daniel's cousin was waiting at home.
5	He opened the door for Daniel then
6	two dogs ran out to greet Daniel.

This prior work has established the foundation for representing text as a causal network and has shown that trained scholars can create these causal networks with acceptable inter-rater agreement [24,25]. We aim to build upon this foundation by assessing if a large group of readers can construct these causal networks with similar reliability.

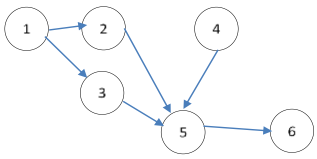

Fig. 1. Causal network associated with narrative presented in Table 1.

2.2 Generate narrative events with the assistance from NLP

Identifying events is a complicated and subjective process, especially when the task is assigned to a group of people. Therefore, we draw upon several techniques from natural language processing to assist this process. Implementing and combining prior research from [8, 9, 20] on NLTK [1], a popular open-source Python package, we build a basic parser that can identify most verbs and the associated subject and object with high accuracy, therefore help consolidating narrative event for this study. The different types of words identified in this step will be further used in the crowdsourcing process. Fig.2 is a sample result of the algorithm when parsing the sentence "Daniel arrived in his aunt's house and two dogs ran out to meet him". However, the algorithm is not error-free, and so we still need to refine the event based on this result.

```
(RRC+VP
  (VBN daniel)
  (VBN arrived)
  (PP
    (IN in)
    (NP
      (PRP$ his)
      (NN aunt)
      (POS 's)
      (NN house)
      (CC and)
      (CD two)
      (NNS dogs)))
  (S+VP
    (VBD ran)
    (PRT (RP out))
    (TO to)
    (VP (VB meet) (NP (PRP him)))))
```

Fig. 2. Parsing result of a simple sentence

2.3 Gathering Causal Networks from the Public on a Crowdsourcing Platform

Historically, creating these causal networks has been both time- and labor-intensive. Our initial pilot data showed that when presented with a piece of text with about 50 events, participants usually spend 30 to 45 minutes to finish the whole process of reading text, identifying events and drawing the associated causal network. Therefore, it is challenging to collect these graphs on a large scale. However, several recent studies have demonstrated that online crowdsourcing is an effective way to perform participatory human research [16]. For example, Amazon's Mechanical Turk has been used in various studies to collect responses from a relatively large group of participants with a range of educational and cultural backgrounds [6,7]. Several studies have also shown that significant information can be extracted from similar platforms about peoples' "real-world" attitudes and behaviors [3,4]. Therefore, we aim to gather causal networks from crowdsourcing workers.

However, simply using crowdsourcing to gather data is not enough. Drawing and removing links between nodes is a slow process regardless of medium, leading to high drop-out rates or inaccurate work. Furthermore, if a network is drawn by hand, saving the graph information digitally can also be labor intensive for researchers. Therefore, to accelerate the process, in this study, we plan to split the crowdsourcing process into two steps: In first step, we ask crowdsourcing workers to verify whether each verb-based event (generated from section 2.2) is indeed a reasonable event; next, we determine the final list of events using evaluation from crowdsourcing worker based on simple-majority rule. In the second step, we design a tool to help crowdsourcing workers to determine the causal relationship between events determined from the first step.

2.4 Designing a tool to assist and accelerate the crowdsourcing process

To make the crowdsourcing process more friendly and convenient for users, we have constructed a tool that can be used to create causal networks and save data simply with a web-browser. The current version of this tool is based on HTML-5, CSS and JavaScript technology, a combination that is especially suited to developing cross-platform tools [17]. More importantly, the tool can directly save the network information into standard JSON data, therefore, granting swift response and data integrity.

3 Sample Output

Fig. 3 is a sample causal network containing 71 narrative events, constructed by a fellow researcher using our tool. It should be noted that all the links are still determined by the participant. The tool doesn't suggest links, instead, it makes drawing and modifying links much faster: drawing links only takes two clicks from one node to another, removing links only takes a double-click on existing links. Fig. 4 shows a screenshot of layout of this tool, which includes the drawing area with the network, the text of the events corresponding to each node, and the information saved in JSON format.

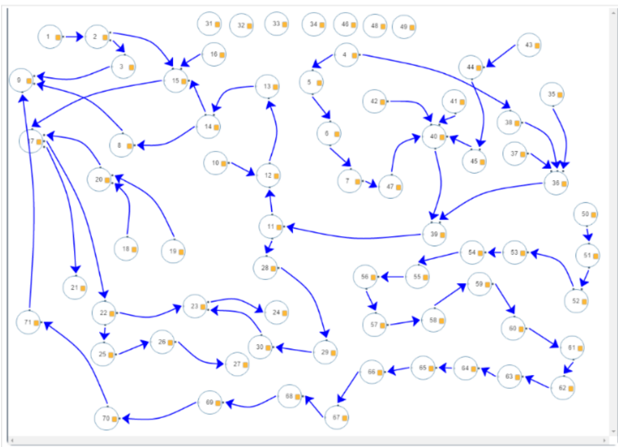

Fig. 3. A causal network created by our tool reflecting 71 events

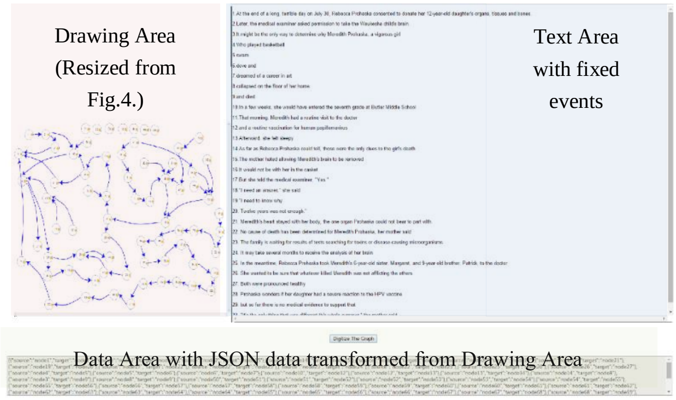

Fig. 4. A snapshot of tool's layout

4 Implications and Future Work

In this paper, we describe the development of a tool that can be used to crowdsource the analysis of narratives. We proposed a systematic and replicable approach to directly measure people's understanding of the causal relationships within each rumor. Network information saved by this tool can be integrated with other popular network analysis software. SNAP [21], for example, can import JSON based data and extract network properties for more in-depth analysis. We therefore aim to continue improving the use cases of this tool to make it more convenient and flexible for scholars and other professionals.

Future work includes performing usability and reliability test using this tool. Eventually we plan to use this tool to determine each suspected rumor's most agreed internal causal network. Building on the rumor's internal network, we would use the approach to test the relationship between the popularity of rumor and the network property of the corresponding rumor's internal causal network. Based on fuzzy-trace theory [22], we hypothesize that a narrative with straightforward internal structure would be more popular compared to a narrative with complicated internal structure.

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