Crowdsourcing the Verification of Fake News and Alternative Facts

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ABSTRACT

Fake news and alternative facts have dominated the news cycle of late. In this paper, we present a prototype system that uses social argumentation to verify the validity of proposed alternative facts and help in the detection of fake news. We utilize fundamental argumentation ideas in a graph-theoretic framework that also incorporates semantic web and linked data principles. The argumentation structure is crowdsourced and mediated by expert moderators in a virtual community.

CCS CONCEPTS

• **Information systems** → *Social networking sites*;

1 MOTIVATION

The phenomenon of fake news and the rise of "alternative facts" have dominated the news cycle of late. Although these terms are new, reliance upon propaganda and misinformation predates the Internet, not just in politics but in communication exchange in general [4]. Critical thinking and evidence-based reasoning are essential for countering propaganda and misinformation intended to manipulate public opinion [9, 10].

Computational approaches for addressing fake news have so far focused mainly on automated tools. These tools flag previously identified hoaxes; or automatically detect fake news articles using natural language processing techniques with pre-existing ground truth; or track the viral-like transmission of hoaxes [2, 6, 8, 11]. None of the existing approaches, however, deal with verification of the alternative facts which constitute the semantic content of such articles.

In such cases, argumentation has been shown to be a natural, substantiated approach for analyzing the veracity and reliability of assertions and claims [3, 7]. In fact, in considering how to assess critical thinking, [3] asserts the need to identify conclusions, reasons, and assumptions as well as judging the quality of arguments and developing positions on an issue. Using this sort of evidence based reasoning not only has the potential to identify fake news to a greater extent but also to imbibe users with the critical thinking ability to navigate future fake news articles.

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In this paper, we present a prototype system that uses social argumentation to verify the validity of proposed alternative facts and help with fake news detection. We utilize fundamental argumentation principles in a graph-theoretic framework that also incorporates semantic web and linked open data principles [1, 5]. The argumentation structure is crowdsourced and mediated by expert moderators in a virtual community. To the best of our knowledge, our novel computational approach is the only one to address the verification of alternative facts and fake news.

2 SYSTEM ARCHITECTURE

In our argumentation framework, a Stance is the final conclusion composed of Claims and Evidence, and their associated Sources. Stances are fundamental stands on a topic and can be mutually exclusive, should have cohesive sub-structures, and are composed of atomic argumentation components (Claims, Evidence, and Sources). A Claim can be directly supported by a Source or have multiple Evidence components, each supported by its own Source. Multiple Sources can support multiple Evidence nodes.

The Sources themselves have their own properties. A Source can be fully described using the Dublin Core metadata[1]. In this way, users could query the system for assertions from certain sources or from sources with specified properties (e.g., government institutions).

Our methodology also incorporates Ratings for each Source and user in the system. Different trust, authority, and other attribute dimensions are amalgamated and weighted in a Summary Rating; these compound ratings reveal their constituent components (SourceRating, ContentRating, QuestionRating, etc.) on a

[1]http://dublincore.org

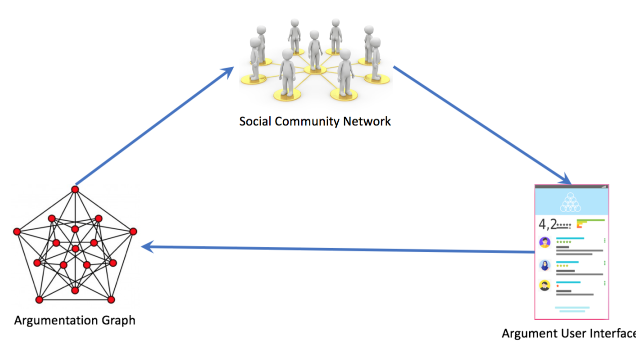

Figure 1: Overview of our System Architecture.

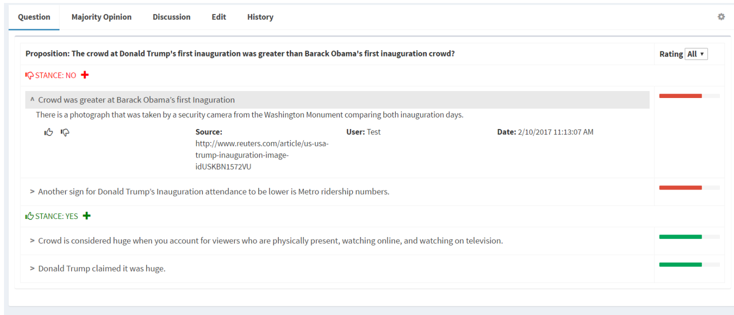

Figure 2: Screenshot of main proposition screen.

MouseOver event, displaying details of Users' Ratings, Source Ratings, Expert Ratings, etc.

2.1 Graph-Theoretic Framework

We create an *Argumentation Graph*, $G_A = (V, E, f)$, composed of a set of vertices, V, edges, E, and a function, f, which maps each element of E to an unordered pair of vertices in V. Each fundamental Claim, Evidence, or Source in an argument thus constitutes an atomic argumentation component, v_a, and is embedded as a vertex in the graph such that $v_a \in V$. The vertices contain not just the component's semantic content, but also the ratings, authority, trust, and other attribute dimensions of each atomic argumentation component. The edges $e \in E$ contain weights along the various dimensions of trust and authority as well as pro/con positions, while the function f maps how they're connected. Depending on the context of the argument, this graph can be undirected or directed, where the temporal component gives the direction to the directed graph.

In terms of a graph, we therefore see the set of vertices V as the set of Claims, Evidence, and Sources; the set of edges E as a set of links that may connect any two vertices. Each subgraph or path traversal that can be obtained from a graph results in a Stance. There are two ways to represent the stances: one way is by making the Stance another node in G_A that is added by the moderators in a top-down manner. The other is to designate each sub-graph as a different Stance. Once he G_A is formed, we can form sub-graphs which represent the different stances we can infer from the argumentation graph where each sub-graph would be a separate Stance. Our approach supports both ways of determining the various stances (what we call top-down vs bottom-up).

2.2 User Interface Component

Our fake news detection system was developed as a web-based application with a responsive interface that allows for viewing on desktops, tablets or mobile phones. The front-end component was developed using HTML, CSS, Bootstrap, jQuery and JavaScript, while the back-end was developed using C# and Asp.net MVC 5 framework. Our front-end connects to the graph-theoretic framework using JSON objects and to the backend using an Object Relational Mapping (ORM) framework. It uses MS SQL as its relational database management system.

2.3 Virtual Community for Crowdsourcing

Our framework is not just a system for argumentation structure; instead, we organize the community and system to work together synergistically to support learning via critical thinking. Members of this virtual community can take three major roles: 1) Users, who are the information seekers submitting the queries; 2) Responders, who have some degree of expertise or background to add Claim, Evidence, and Source nodes; and 3) Moderators, who are contributors that guide the question and answer flow, including triaging incoming questions, matching experts to new questions, evaluating answers for quality assurance, etc. These roles are dynamic as they may evolve over time, and may be multi-faceted with different functions and capabilities.

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