An Ontological Approach to Misinformation: Quickly Finding Relevant Information

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Abstract

Identifying misinformation (i.e. rumors) is a growing field of research in the information systems field. This is due to the fact that during recent tragedies (i.e. Boston Bombings, Ebola, etcetera), rumors spread rapidly on social media platforms, which will hide the facts about an event. This results in rumors being spread even more, further hiding the events. In this study, we draw from research from the semantic web to tackle this problem. We propose the use of ontologies and related concepts can help find accurate information for a case quickly and accurately. Combined with a weighting formula, we will be able to display the most relevant results to an interested party. In this research in progress, we outline our plan on how to accomplish this once an ontology and dataset is found.

1. Introduction

It is an ongoing issue that there are a lack of sufficient methods to allow for automated analysis of publically available data in order to anticipate or detect societal events, such as political crises, mass violence, and riots [7]. This has only continued to become a larger issue as social media continues to cover disaster events. For example, during the Boston bombings in 2013, there were many informational messages on Twitter to update the public on the situation. However, there were also a lot of rumor related messages that caused widespread panic [13]. Therefore, it became extremely difficult for people to realize what messages they should pay attention to.

The Boston Bombings in 2013 are not the only case where panic has occurred due to misinformation being propagated, but it is one of the more famous examples [14,21]. However, it helps show that there is currently no way to detect when misinformation is causing panic, or how to prevent it. As a result, both governments and academia are concentrating on this issue. Therefore, the objective of this paper is to discover a way to help facilitate earlier discovery of ongoing events than currently exists. We propose that an ontology can help solve this issue. Ontologies have been extensively used in other research areas, such as the semantic web domain [9,10]. Previous research in the semantic web domain has concentrated on how to discover information that search engines normally miss, and one solution is to use ontologies to help speed up the process of finding relevant information. Additionally, ontologies can help find information that is normally lost. For example, previous research has combined a domain-specific ontology, such as one for the FBI, which allows information such as common terminology, slang, and case-specific information to be prioritized and found [10]. While this previous research was used on a mailing list, such a concept could be extended to the misinformation field. Since ontologies are graphical and hierarchical in nature, this allows an intuitive view for examining information, especially if output is done in a similar manner. For example, during the Boston Bombings in 2013, if each suspect had their own node in an ontology, all relevant information could be created in additional children nodes. As more pertinent information emerges, the relevant nodes could be weighted differently, such that more critical information stands out more. If this can be done quickly enough, then when children nodes that may not make sense start being created, then this can be an indicator that misinformation is occurring.

The first research question that will be addressed is how this ontology can be created. This will require leaving the traditional IS research and expanding to other fields of research, such as semantic web and information retrieval fields, and seeing how this can be brought into the IS field. The second research question is how to weight the ontology such that the most pertinent information is brought to attention earlier than they would normally find. If these can be tackled then current threats can be identified sooner,

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then the potential contribution would be to help find critical issues earlier such that they can be mitigated.

The rest of this paper is as follows. First, we will go over the literature review over relevant literature including ontologies, misinformation, and social networking sites. Then the model for the paper will be introduced, followed by the introduction to the hypotheses. Finally, the proposed methodology will be reviewed, followed by the expected contributions and limitations of the research.

2. Literature Review

In this section, we will discuss the literature review for our paper. First, we will outline how social networking websites are used during crises to circulate information, including misinformation. Next, we will then review the literature that has proposed various ways on how to limit the about of misinformation that is propagated during these crises. With this in mind, we then move onto our literature review about ontologies. In this section we will discuss what an ontology is and how it has been used primarily in the information systems field. We will then discuss previous literature that have created specific ontologies for various purposes, such as creating a common body of knowledge for a domain, or helping improve finding domain specific information. We then conclude on how to weight ontologies when appropriate to help further find relevant information.

8.1. Social Networking Websites and Limiting Misinformation

Social networking websites are often used during crises such as earthquakes, bombings, wildfire [13]. However, one of the largest issues in this area is how does someone prevent rumors from being disseminated more than fact, which results in more panicking and issues during these crises. This is called misinformation, and there has been extensive research done on this. One of the earliest works that dealt with misinformation (i.e. rumors) being propagated on social media websites was Nyguyen et al.'s work. [19]. In this work, the authors work on identifying the sources of misinformation by studying the k-Suspector problem. The k-Suspector problem aims to identify the top k most suspected sources of misinformation, and to do this they used a ranking based and an optimization based algorithm [19]. Using real-world datasets, they found that their algorithms allowed them to trace back the sources of misinformation with high accuracy [19]. They then continued their work to discover how to limit the viral propagation of misinformation by tackling the bI-Node protector problems [20]. This problem aims to find the smallest set of highly influential nodes where good information helps contain the viral spread of rumors within a given time period T [20]. They created a greedy algorithm, which grabs the most influential nodes to help limit rumors, and using real-world traces discovered that their algorithm out-performs alternative approaches in finding which important nodes can help contain the spread of rumors [20].

Starbird et al. investigated a similar issue of whether crowd sourced information, such as Twitter's tweets, can correct misinformation [24]. They found that while rumors do circulate on social media sites, such as Twitter, corrections to the rumors do emerge. However, the primary issue is that these corrections are muted compared to the original rumors. They saw preliminary evidence that there may be patterns in the rumors and corrections to the rumors, and suggest that future research may be able to automatically detect rumors due to this. This inspired a recent study in the social networking realm, which examined the impact of tweet features on the diffusion of rumor and non-rumor related messages during the 2013 Boston marathon tragedy [13]. The purpose of this study is that rumors in real time events, such as the Boston marathon tragedy, can cause a lot of harm. Therefore, it is critical to try to identify what messages are rumors and limit their propagation. Therefore, they wanted to discover which parts of a Tweet were more likely to be correlated with rumors. Using a negative binomial analysis, they found that the number of followers had a positive correlation with message diffusion, tweet reaction and message diffusion had a negative relationship, and tweet messages that did not include hashtags diffused more than messages that contained hashtags [13].

However, the Boston bombings are not the only tragedy that has been studied recently. A different study concentrated on Ebola tweets on Twitter from late September 2014 to late October 2014, then applied the SEIZ (susceptible, exposed, infected, and skeptical) compartmental model to the information propagated [8]. They argue that the SEIZ model is ideal for information propagated on twitter as it compartmentalizes users into four categories: susceptible (S) users who haven't received the information, exposed (E) who have received the information but haven't tweeted about it, infected (I) users who have received and tweeted the information, and skeptical (Z) users who have received the information but chosen not to tweet it [8]. They discovered that news stories have higher response ratios than rumors, at least for the Ebola tragedy. However, they did discover that two rumors, particularly the rumor that Ebola was airborne, had elevated response values which suggests greater belief in these rumors. Therefore, at least for this tragedy, rumors were not such an issue. This could be due to the fact the Ebola crisis was a much longer crisis than the Boston bombings (i.e. a month versus a few hours for most of the information).

8.2. Ontologies in IS

Ontologies are an understudied area in the information systems (IS) field. Previously in IS, ontologies have been defined as strategic objects to serve as foundations for strategic patterns or technological patterns [18]. Previous literature has provided a good definition of what an ontology is, which is "a vocabulary (a set of words), a grammar (the set of rules for combining words into larger structures), and semantics (the meanings of the words and the larger structures) all defined within a specific domain." [18]. Ontologies are often created to help standardize the terms used to represent knowledge about a domain [18]. Since this introductory paper for ontologies and IS, ontologies have been increasing in popularity in the IS field.

For example, research was done to help describe the concept of ontological design and show how they can be used as maps of complex, ill-structured problems [23]. They argue that ontological analysis is a method for capturing a problem's complexity, such that the dimensions of the problem and the taxonomies of these dimensions are logically derived from the statement of the problem [23]. Rather than use ontologies to represent concepts as they are traditionally used, this research used it at a higher level of abstraction and granularity, to create more of a strategic ontology [23]. This research was then continued by developing a method to collaboratively develop an ontology about the student lifecycle management system [22]. This ontology was then used in a class to help model a problem and design a solution. Users found it to be comprehensive, insightful, and useful [22]. While this is not the use of ontologies in this paper, it helps show how ontologies are used previously in the literature.

However, there has been research done in the IS field that is more traditional in how ontologies are used compared to the semantic web research. There has been some research done in the development and use of ontologies such as e-government services to help identify goals and activities of administrators and citizens and businesses for e-government [11]. Ontologies have also been used to help augment use cases with semantic information in software development [2], computer security [5], and e-learning [15]. These ontologies have been creating using various methods such as activity theory [11], simply extending existing ontologies [2,15], and extending taxonomies [5].

There has also been research done to convert ontologies into more well-known IS objects, such as Bayesian networks in data mining [4]. Bayesian networks work very well as they are also a graphical model used for knowledge representation and allow for some uncertainty [4]. This has been extended for the medical diagnosis arena, where medical ontologies were converted to Bayesian networks to allow for probabilistic analysis [1].

8.3. Specialized Ontologies

The most similar ontology to what our paper is inspired by is a law enforcement ontology that was created throughout a three-year project [10]. In this project, the authors had access to a database containing conversations form a Listserv from the Federal Bureau of Investigation (FBI). From this, they were able to find high level concepts such as person, organization, event, and place. They then found specific subclasses from these high level concepts such as weapons, a suspect's information, and FBI specific acronyms. From this, they were able to create an ontology. One of the most interesting extensions to their ontology was to add a thesaurus to help support extraction of named entities from free text, along with specialized rules to associate full names with partial name references [10]. One of the most important aspects to take away from this study is that to develop such a highly detailed ontology specific toward the FBI was a three-year project, which is nontrivial. Therefore, it is important that time spent to develop an ontology is done so wisely, so no time is wasted.

8.4. Weighting Ontologies

The final section of our literature review will discuss weighting ontologies. Weighting an ontology allows certain things to be more important, so in cases such as murder, a rare murder weapons may be more important than things such as gun safes. The primary article that has tackled this issue was done so by Tar and Nyunt [25]. They had four assumptions: the more times the word appears in the document, the more possible it is a characteristic word, the length of the words will affect the importance of the words, if the probability of one search term is high, then the word will get an additional weight, and one word may be the characteristic word that is desired even if it doesn't appear in the document [25]. This leads the following formula:

W = length x Frequency x Correlation Coefficient + Probability of Concept [25].

W is the weight of the keywords, length is the length of keywords, frequency is times which the words appear, and if the concept is in the ontology, then correlation coefficient=1, otherwise correlation coefficient=0. Probability is based on the probability of the concept in the document. The probability of the concept is estimated by following equation:

P (concept) =Number of Occurrences of the Concept / Number of Occurrences of all the Concept [25].

In this literature review, we have seen the research conducted in misinformation and ontologies in multiple domains. Previous studies in misinformation have had solutions that do not help investigators find information about a certain individual, but simply sort misinformation from information. Additionally, they may only help show misinformation and information in hindsight, and do not help investigators with answers as needed. Our study differs as we are able to provide real time information if an existing ontology already exists. Additionally, we will be able to help show more than if information is a rumor not, instead we will be able to rank the information from most important to least. This way, using the ontology, we can further emphasize information such as suspect names and information related to them.

With ontologies, previous studies in the IS field have used ontologies to help standardize terms, or used to create patterns. Our study differs from this as while we are helping standardize terms or introduce terms, we are extending this idea to also provide information that should will help find information in a dataset. We will also combine a thesaurus and ontology weighting to achieve this goal. Simply put, our study will be doing more than simply identifying if information is misinformation or not – we will be providing information to investigators or people on what is most important about a case.

3. Model Development

The model for this paper will now be introduced. The model has four constructs: an ontology, a weighting formula, a thesaurus, and a dependent variable which we call information found. The construct ontology is simply a specialized ontology for a domain. In this paper, the domain for the ontology is regarding misinformation, such as terrorism. The primary focus should be on a specific area of misinformation management, which will heavily depend on where data can be obtained. Since this ontology needs to be created in order to be domain-specific, what ontology we use highly depends on the dataset that is obtained. Therefore, we will concentrate on a social media website, such as Twitter, where data can be collected easily and a new ontology can be created. This combined with a recent act of terrorism, such as the shooting in Orlando, Florida. For the weighting formula, we can simply use the one discussed in the literature review and test it to verify it works for our ontology.

The thesaurus construct is inspired by Johnson et al.'s work, to help further expand the ontology. This way the ontology does not get bogged down by synonyms or other similar words. This thesaurus will most likely use WordNet to help with this matter. Finally, the dependent variable is information found. Information found is whether some information is misinformation (i.e. a rumor) or correct information. All of this relies on a specific event occurring, which will depend on when the ontology has been created and if there are any crises occurring near the time the ontology will be created. The ontology will either be found from existing literature, or developed using action theory. The proposed model can be seen in Figure 1 below.

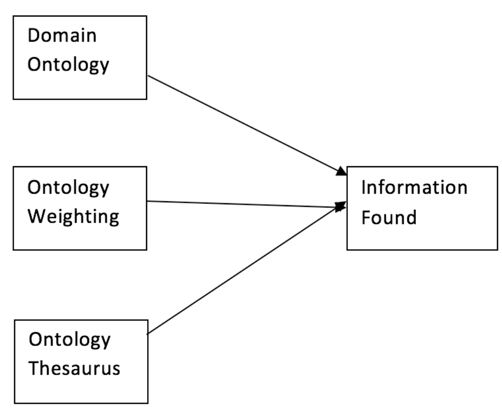

Figure 1. Proposed model

4. Hypotheses Development

In this section, we will introduce the hypotheses for this paper. First, we remind the reader that ontologies have previously been used to help augment use cases with semantic information in software development, computer security, and e-learning [2,5,15]. Since these previous work showed that ontologies can help improve finding information, we introduce our first hypothesis:

Hypothesis 1. The use of a domain ontology will positively influence the information found in a particular domain.

While hypothesis 1 is a bit intuitive, there has been a lack of study on this relationship in the IS field. Therefore, it is critical to make sure this still holds in a new domain. With this domain ontology in mind, it is important to remember that ontologies are typically used to simply represent relationships, such as a cat is an animal, a road is a type of infrastructure, and so on. Therefore, while a domain ontology may allow us to find additional information that we may normally not be able to find, it also may cause us to find too much information. Therefore, in order to help find more relevant results first, ontology weighting will help fix this problem. This leads to our second hypothesis:

Hypothesis 2. The use of an ontology weighting formula will help improve the information found, such that those results ranked higher are more relevant information.

While using an ontology thesaurus is not original, it has not been done in the context of a weighting formula as well [10]. This combined with the fact that it is not a common technique for ontologies to use a thesaurus means it is critical to test the influence an ontology thesaurus has. We argue that the use of such a thesaurus will help return more relevant results. Therefore, our third and final hypothesis is as follows:

Hypothesis 3. The use of an ontology thesaurus will positively influence the information found in a particular domain.

5. Proposed Methodology

Now that the hypotheses have been introduced, we move onto discussing the proposed methodology for this research-in-progress. First, it is important to consider the data sources for all the hypothesized relationships. The primary dataset needs to be considered. A dataset is needed that contains a large amount of information that needs to be parsed through. Additionally, there needs to be some sort of target that we are searching for in this dataset. Ideally, this dataset will have a primary topic (i.e. terrorism, hacking, etc.) with an existing ontology. Therefore, the goal is to test this on an existing dataset that has been studied previously, so we will be using the Boston Bombing twitter dataset. This dataset has existing known truth, and known differing levels of importance of information. Once this has been tested, we can re-do it on a study that has not been studied as extensively, such as recent crimes.

To create this dataset, we will first need to collect the Tweets. Previous research has generally created a custom tool which uses the Twitter Streaming Application Program Interface (API) [13]. Alternatively, if the event has already occurred, and has happened too long ago, then we can use a third party service to find the tweets. Previous research has used Topsy, which stores historical Tweets and indexes them for searching [13]. Once all relevant tweets have been collected, we can then search the Tweets using keyword searching. These keywords will vary depending on the case that is analyzed. As previously mentioned, we want to compare to existing studies, and therefore we are intending to compare to the Boston Bombing event. As a result, we will have to use a third party service, since the Tweets will no longer be available through the Twitter API. To compare to previous studies, we will use the following keywords: boston, bostonmarathon and bostonbombing [13]. From these tweets, we can then collect relevant fields such as the content, user name, Tweet time, and Tweet ID [13]. Once we have this dataset, we will use it as input to test our ontology.

For the ontology itself, we are searching for an ontology that is extremely detailed, such as the one discussed in the literature review [10]. In the event this is not possible, there are ontologies that are not as extensive available [3]. DARPA ran a program between 2000 and 2006 to help develop a language and tools to facilitate the concept of the semantic web [3]. Within this compilation of ontologies, there are very basic ontologies that have been developed. There are ontologies that could be useful such as ontologies developed for terrorists and security [3]. However, even with these ontologies, they are too simple for our purposes. Therefore, we will need to use a dataset to help improve the ontologies. In order to extend the ontology, we will follow the guidelines provided in previous literature [16,26]. Important aspects from previous literature includes identifying what moments and events are [16]. Events are describing various events at a particular part in time, including things such as the date, the event that occurred, people involved, and etcetera [16]. Moments are a more detailed, more specific, smaller unit of something that occurred in a particular moment of time [16]. It will also be important to help develop relationships, which will again depend on the dataset [26]. Therefore, one of the other critical components of building the ontology will be finding others who are familiar with the domain, to help create the ontology. There will need to be agreement on the events, moments, relationships, and other terms defined. If the ontology has to be created/expanded, the ideal dataset will be the Mumbai Terrorist attack in 2008 [21]. Similar to the Boston Bombings, this is another attack against many people that occurred without warning. It has also been studied in previous literature, also through collecting Tweets. Therefore, there is enough similarities to help create an ontology.

For the thesaurus, one will have to be developed. To facilitate this, WordNet will be used to help automate the finding of synonyms of words in the ontology [17]. It is not known how extensive this would be, instead testing would have to be done to discover what the optimal amount is on a test dataset to discover how large the thesaurus needs to be. In previous literature, only noun, adjective, and verb synonymous were created [10]. Also, the authors hinted that only a subset of all synonyms were used [10]. Therefore, we can limit the amount of each of these to be five synonyms, for a total of fifteen, to provide an additional thesaurus. If this is found inadequate, more can be added at a future date. Finally, the weighting equation does not require a dataset – instead it will be fine-tuned at the same time of thesaurus development.

Since this experiment is design science oriented, no surveys or scales will be used. Instead, once everything has been created, we will simply compare our results for the Boston Bombings dataset with previous results from existing literature. This section concludes with Table 1, which provides an overview of the constructs defined in this paper.

Now that we have discussed how we plan to create our experiment, it is important to briefly mention the measurement methods and statistical techniques that will be used to test the hypotheses. Since our primary goal is to see whether or not we found misinformation (i.e. information found), this results in a dichotomous dependent variable. As a result, logistic regression may be optimal for our experiment [6]. We will run the Spearman rank correlation test to verify there are no multicollinearity problems. Logistic regression will also let us see how much impact our independent variables have, allowing us to test our hypotheses. Finally, we will verify that we have a large enough dataset of Tweets, to minimize Type II errors. Type 1 error can be minimized by using a p-value of 0.05 or below [12]. This is important, as the dataset will have false negatives that could be worsened by the limited amount of content available in a Tweet.

Table 1. Overview of constructs

Construct	Definition	Main References
Domain Ontology/ Ontology	A vocabulary, a grammar, and semantics all defined within a specific domain.	[18].
Ontology Weighting	The method in which the terms in an ontology are weighted, such that a higher number corresponds to being a more important/relevant term.	[25]
Ontology Thesaurus	A list of words in groups of synonyms and related concepts	[10]
Information Found	Whether or not relevant information to a specific topic is found.	[10]

6. Conclusion

In this paper, we have developed a case for why ontologies need to be brought in to the IS field. While this paper focused on the domain of misinformation, ontologies can be brought to other aspects of IS as well, almost any domain where big data is applicable. Our biggest potential contribution will be bringing a new methodology to discovering relevant information that is normally lost in large datasets. This can then allow an investigator to find information earlier than before, possibly reducing the amount of damage done. Additional contributions include bringing an ontology, an ontology thesaurus, and weighting formula all together for the first time in the IS field.

However, due to the fact this is a starting point in this new field of research, there are potential limitations and places for future work. Our biggest limitation will be what ontology we are able to use. More useful research will occur if an ontology that has already been extensively developed is obtained, rather than using a small ontology or one that is created. Additionally, while it would be ideal to display output to an investigator in a manner similar to an ontology (i.e. a graphical view), it is outside the scope of this work. Instead, the focus of this paper is how to find the relevant information. This is accepted as a limitation. A final limitation is that this proposed method will not work in real time due to the ontology requirement and the need to find such an ontology. This makes it so as a real life case occurs, the ontology would need to be created quickly in order to be useful for real time. Therefore, we suggest that more work in ontologies occur so that these can easily be compiled and used in real time.

There are two primary aspects for future research. First, we are not fully utilizing the design science potential of this experiment. Therefore, future studies include re-structuring the research by adopting a design science research framework. This would allow us the potential to discover a design theory. Finally, additional future research includes assessing the components of this research separately. This will help in allowing to see if there is overlap in our research, and provide a better idea on what can be improved upon.

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