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Methods for assessing the credibility of volunteered geographic information in flood response: A case study in Brisbane, Australia

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A R T I C L E I N F O

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A B S T R A C T

Volunteered Geographic Information (VGI) has been widely adopted to assist in disaster management, yet its characteristics of uncertainty and requirements of large amounts of manual manipulation for data validation and interpretation hinder VGI applications. In this study, we aimed to develop an effective method to assess the credibility of VGI for time-critical conditions, such as disaster response. We collected datasets from two extreme flood events in 2011 and 2013 from Brisbane, Australia. According to the defined geo-location factors, we built a binary logistic regression with the 2011 event dataset to measure the credibility scores of the VGI instances. At the threshold of 0.917, the overall accuracy of the model in the 2011 training dataset was 90.5%. Next, the performance of this probability model was evaluated by the 2013 testing instances. We found that our model could categorize the credibility classes with 80.4% accuracy. These results suggest great potential for our model to be used by emergency management sectors to sort credibility of VGI for efficient and rapid response, decision-making, and coordination.

1. Introduction

With the rise of online mapping services and GPS-enabled communication technologies, geographic information observed by the public can be shared in highly flexible ways. People without professional cartographic skills or knowledge can report their geographic positions and even make thematic maps on interactive mapping applications (e.g. OpenStreetMap[1]). This phenomenon, termed Volunteered Geographic Information (VGI), refers to the access, provision, and dissemination of geographic information by volunteers *via* the use of Internet (Elwood, Goodchild, & Sui, 2012; Goodchild, 2007). In disaster management, VGI can be important and complementary to the data collected by official sectors. Taking the response to Hurricane Katrina in 2005 as an example, people were faced with government failure and therefore bypassed official agencies to render assistance spontaneously (e.g. Katrina People-Finder Project, Google Maps mashup at Scipionus.com, see: Kawasaki, Berman, & Guan, 2013; Miller, 2006).

A pivotal application of VGI in crisis management is the mapping platform (e.g. the Google Maps application, or the Ushahidi[2] platform), which is used to identify and communicate disaster information (Coleman, Georgiadou, & Labonte, 2009; Meier, 2012). Such a platform involves two different types of "crowd": (1) a geographically affected "crowd" to provide raw information directly, and (2) a remote, volunteer "crowd" to coordinate and manage information in support of a humanitarian response (Starbird, 2011). Although VGI gathered *via* this approach has been applied to the response to extreme events such as the 2010 Haiti Earthquake and the 2011 Queensland Floods (McDougall, 2012; Zook, Graham, Shelton, & Gorman, 2010), the characteristics of uncertainty and insufficient details significantly hinder its utilization (Posetti, 2012; Schade et al., 2013). Time-consuming and error-prone amounts of manual manipulation are required for validating VGI reports and quality (Morrow, Mock, Papendieck, & Kocmich, 2011; Potts, Lo, & McGuinness, 2011). Involvement of vandalism or false information in VGI is always a major concern (Ford, 2011). Prior studies addressed the quality issues associated with VGI in disaster management (Goodchild & Glennon, 2010). Development of automated methods for credibility assessment of VGI is a formidable challenge to improve its use

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[1] http://www.openstreetmap.org/, accessed 01 April 2015.

[2] https://www.ushahidi.com/, accessed 15 October 2015.

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in disaster management. Here, we aim to utilize a probability model based on the data of locations and spatial distribution of VGI to assess the credibility of the VGI instances. We collected geo-referenced VGI from two crisis mapping platforms and developed a binary logistic regression model for mapping the VGI instances to the predicted credibility classes.

The remainder of this work is articulated as follows. Section 2 provides a review of methods for VGI quality assessment. Section 3 outlines the approach and methodology for building the proposed model. In Section 4, we describe the processes of VGI raw data cleaning, and labeling the data for model development. Section 5 describes the details, results, and evaluation of our developed model. In Section 6, we discuss the advantages and limitations of the developed methods, as well as the future research plans. Section 7 concludes this study with consideration of larger implications.

2. Methods for quality assessment in VGI studies

Methodologies of VGI quality assessment include two perspectives, quality-as-accuracy and quality-as-credibility (Bordogna, Carrara, Criscuolo, Pepe, & Rampini, 2014; Flanagin & Metzger, 2008; Poser & Dransch, 2010; Spielman, 2014). In quality-as-accuracy, the methods examine the accuracy of VGI contents by data quality elements, such as positional accuracy and thematic accuracy (ISO, 2013; Oort, 2006). Researchers have used methods of comparing VGI with authoritative data or modeling results to estimate the accuracy of VGI (e.g. water level), and pointed out that VGI data have the potential to be as accurate as authoritative information (de Brito Moreira, Degrossi, & de Albuquerque, 2015; Poser & Dransch, 2010). However, these methods have limitations, including the availability and accuracy of reference data. Access to authoritative data is often under contradictory licensing restrictions or has a high procurement cost (Antoniou & Skopeliti, 2015). In addition, several experiments used trained volunteers for ensuring accuracy but with mixed results (de Brito Moreira et al., 2015; Lee, 1994). Still, some attributes (e.g. flow velocity) cannot be accurately assessed by human beings (Poser, Kreibich, & Dransch, 2009).

On the other hand, the methods of quality-as-credibility examine VGI with perceived truth based on its characteristics (Flanagin & Metzger, 2000, 2008). Relevant methodologies for credibility assessment have been discussed in the literature. Hall, Chipeniuk, Feick, Leahy, and Deparday (2010) and Goodchild and Li (2012) suggested the use of crowd intelligence to validate and correct errors (the crowdsourcing approach), or appointing senior volunteers as gatekeepers (the social approach). These two approaches are both applicable for assessment of accuracy and credibility. Relevant methods include assessment of information quality based on reliability and reputation of contributors, or using comparison methods for cross-validation. However, these are inefficient when facing extreme events, as manual process is time-consuming. Field assessments for cross-validation may be necessary (e.g. Westrope, Banick, & Levine, 2014).

Although manual assessment often is regarded as a subjective perception of data users, subjective judgment can be based on objective components (Flanagin & Metzger, 2008). To lessen manual intervention, automated methods have been discussed in the literature. A major challenge to automated methods is to recognize and interpret the specific pattern of objective components in VGI. For example, prior studies investigating components such as text contents and information sources, adopted techniques of information retrieval such as Supervised Machine Learning (SML) to sort social media messages during crisis events (Castillo, Mendoza, & Poblete, 2011; Gupta & Kumaraguru, 2012; Morris, Counts, Roseway, Hoff, & Schwarz, 2012). The SML methodology requires to label raw data, and to identify important features (e.g., length of messages or number of retweets) for modeling and training classifiers. However, SML methodology often does not consider the aspect of geographic information and is limited for further usage. By fusing existing geographic knowledge and information, the spatial dependence between VGI and other geographic data can be investigated in a geographic approach or an aggregation approach (Dransch, Fohringer, Poser, & Lucas, 2013; Goodchild & Li, 2012; Schade et al., 2013). For example, a wildfire incident has increased credibility, if similar reports are submitted nearby and located in a district of a high ratio of vegetation cover. Therefore, measuring credibility of VGI can be gauged from geographic context and spatiotemporal proximity to risk areas or other VGI data (Craglia, Ostermann, & Spinsanti, 2012). This methodology has been examined in a series of studies focusing on the detection of disaster events from social media, to help first responders gain situational awareness during a disaster. However, it is difficult to convert the aggregated information into quantitative measurements (De Longueville, Luraschi, Smits, Peedell, & Groeve, 2010; Ostermann & Spinsanti, 2012; Spinsanti & Ostermann, 2013). Among these, Spinsanti and Ostermann (2013) developed a method with scoring functions for credibility assessment in a forest fire case study. However, the threshold values of the functions are difficult to justify, and could be further refined.

Moreover, investigation of the geo-location credibility was proposed to couple with the analysis of the text contents or information sources. Bishr and Mantelas (2008) developed a model for quantifying credibility assessment by merging trust and reputation of social networks with spatiotemporal characteristics of contributors and information consumers. Nevertheless, this method is not quite applicable in disaster response, as contributors might not have an online reputation. Truelove, Vasardani, and Winter (2014) examined linguistic style with direct observation or specific terms of social media messages to develop a typology for identifying witnesses or affected people. But this method requires automation, and the utilities of the typology are still questionable.

Table 1 summarizes the approaches and methods of credibility assessment of VGI in prior studies. Among these, the geographic approach using spatial pattern analysis could be helpful for emergency stakeholders in a quick response to an unexpected event. However, the current available methods are not flexible enough to identify the geographic factors and variances which have impact on the credibility. These limitations hinder the VGI applications in emergency stakeholders. There was a clear need for developing automated models that can accelerate the process of credibility assessment. In this study, we adopted the concept of SML methodology and applied the geographic approach to develop a probability model for the geo-location credibility assessment in a case study of flood response.

3. Research approach, methodology, and data collection

3.1. Overview

Using a case study approach, our methodology includes the following 5 steps: (1) defining the study area and data collection: gathering the VGI flood incidents from two applications in different events (2011 floods as the training dataset and 2013 floods as the testing dataset) in Brisbane, Australia, (2) data cleaning, for exclusion of data with inaccurate positioning, (3) labeling credibility classes of incidents in the training dataset and analyzing their spatial distribution by mean nearest neighbor analysis, (4) developing a binary logistic regression model by non-real time