Introduction

Digital humanities research is characterized by values of transparency and collaboration through online networks (Spiro 2012, p17). This means that digital humanities can contribute to fields of work beyond academia, such as in humanitarian disaster responses. Visual media data shared during disasters are a source of information for humanitarian responses and research. They can also be a source of information for digital humanities researchers. This data can inform acute emergency responses as well as longer term research to prevent and mitigate future disasters. Given the time dependencies and short funding cycles of disaster response work, the digital humanities can support humanitarian activities through longer term research and analysis that may have academic and humanitarian outcomes. This chapter shares a real-world case study of humanitarian-driven imagery analysis using open-source crowdsourcing technology. Potential links to digital humanities are emphasized, with the hope that in future, data analyses and academic work in digital humanities may be able to support humanitarian goals.

GeoTag-X was developed at the United Nations Institute for Training and Research (UNITAR) Operational Satellite Applications Programme (UNOSAT) in Geneva and built using the Pybossa open source crowdsourcing platform. It was funded through the European Commission 7th Framework Programme for Research and Technological Development as part of Citizen Cyberlab. The broader Citizen Cyberlab research project aimed to research and evaluate online collaborative environments and software tools for creative learning. Most other applications were focused on citizen science; GeoTag-X was unique in its humanitarian disaster response focus.
GeoTag-X aims were aligned with best practices in humanitarian knowledge management (King 2005; Cervigni and Smith 2014):

- identify media relevant to a disaster or emergency that are not already being categorized and geotagged;
- analyse content to generate associated metadata for sharing, pooling, comparison, verification and mapping;
- establish a community of practice involving individuals in multiple organizations to develop tacit knowledge associated with explicit knowledge generated through the project and with the knowledge of other organizations;
- focus on geotagging, to facilitate visualization and accessible representations of complex data and information;
- prototype humanitarian application of an open-source crowdsourcing platform and use prototype data and information to answer questions and respond to identified information needs;
- recognize the value of tacit knowledge gained from field experience, collaboration and learned expertise;
- research if and how such knowledge can be passed on to new digital volunteers;
- promote the use of GIS technologies and internet technologies, including PyBossa for open-source crowdsourcing and GitHub for virtual collaboration and version control.

These aims yielded data designed for use in humanitarian disaster response contexts. The project’s open philosophy meant that outcomes could also contribute to digital humanities projects, given open licensing supports uses unanticipated by original users.
Aims of the project were drawn from the Information Systems for Crisis Response and Management (ISCRAM) community (Van De Walle and Turoff 2006), through which related technologies have been documented. Existing research anticipated system development needs, for example challenges in data storage and integrating new social media sources (Schram & Anderson 2012). Complementary systems existed to support disaster responses, for example an Australian system developed in collaboration with official crisis coordination teams. This system was motivated by a 2009 Australian Royal Commission on bushfires, which heard evidence that official services lacked information reported in near-real-time on social media (Yin et al. 2012, p54). Another system used mobile phone calling data to inform emergency responses (Madey et al. 2006). GeoTag-X differed from existing systems in focusing on crowdsourced imagery coding and analysis, as well as having an explicitly open ethos, of relevance for digital humanities research.

ISCRAM research can be described as crisis informatics, which has been defined as the study of social, technical and informational concerns in emergency response. This includes interactions and concerns of formal responders as well as affected citizens (Palen et al. 2010; Starbird et al. 2012; Cervigni and Smith 2014, p8). Discussion about the value of volunteer participation in disaster responses reflects collaborative and crowdsourced values of digital humanities, as well as debates about how to value expert knowledge (Spiro 2012, p20).

By viewing the citizenry as a powerful, self-organizing, and collectively intelligent force, ICT has the potential to play a remarkable and transformational role in the way society responds to mass emergencies and disaster. Furthermore, this view of a civil society that can be augmented by ICT is based on social and behavioral knowledge about how people truly respond in disaster, rather than on simplified and mythical portrayals of people unable to help themselves. Research has shown that disaster victims themselves are the true first responders, frequently acting on the basis of knowledge not available to officials (Palen et al. 2010, p1-2).
Debates about the merits of expert and public contributions are shared across digital humanities and humanitarian disaster response work.

Crowdsourcing is a form of volunteer participation. The speed and willingness that digital volunteers have shown in collecting and compiling information in disaster responses has already influenced the United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA). Digital volunteers have helped to collect information for relevant datasets much more rapidly than officials could alone, with huge potential impacts on officials’ responsibilities in information management (UNOCHA 2011). Crowdsourcing can involve people feeling a need to help (Lowe and Fothergill 2003) who might not have opportunities to help in other ways.

However, crowdsourcing remains controversial. Research has questioned the ethics of crowdsourcing from the perspective of employees’ rights (Felstiner 2001), which is mitigated in humanitarian disaster response circumstances in which people volunteer regardless of crowdsourcing (Finkelstein & Brannick 2007). Crowdsourcing challenges the privileged role of individual experts (Spielman 2014). Research has indicated that unpaid crowds can produce results of high quality regardless of the type of task (Borromeo et al. 2016. A systematic review of crowdsourcing in health and medicine found that it can improve the quality of a research project, as well as increase speed and reduce cost - however also called for standardized guidelines on crowdsourcing metrics and reporting methods for clarity and comparability (Ranard et al. 2014). This call is consistent with principles of open research, to which discussion of the GeoTag-X method is intended to contribute.
Method

The name GeoTag-X expressed key components of the system:

1. *Geo*: all media should be georeferenced as accurately as possible;
2. *Tag*: all media should have metadata relevant to the humanitarian and disaster response community, compatible with existing disaster response methodologies;
3. *X*: the system should be adaptable for diverse disaster situations anywhere in the world.

An early iteration of the platform in 2011 was called CyberMappr (Bromley 2012), which engaged volunteers in finding and georeferencing online photographs depicting damage resulting from conflict.

Source code for the GeoTag-X project, which was adapted from the open source Pybossa code, is available at github.com/geotagx. This includes code for the overall website as well as specific projects, modules and tasks. A project is typically a disaster event, such as the 2014 Ebola outbreak in West Africa or flooding of the Yamuna river in India in 2013. Modules are analyses of imagery that forms a dataset associated with a project. For example, the Ebola outbreak project included a module about analyzing images for responders’ use of personal protective equipment. Another Ebola module was about geotagging the images. The Yamuna project included modules about analyzing flood waters and pollution, as well as separate modules analyzing impacts on people and animals. Tasks were individual analyses of images within modules. Task design reflected that of the underlying Pybossa code.
GeoTag-X was designed so that new modules with different questions could be flexibly developed depending on human input in response to environmental conditions, typically a new disaster event. This meant the system had potential to reflect a diverse range of values and cultural perspectives. Rather than claiming to be a neutral, anonymized data analysis platform, GeoTag-X transparently communicated humanitarian values and objectives through descriptive text. Participants could consider for themselves the questions used in the system and could contact developers to suggest new modules or projects asking different questions. This is why GeoTag-X was framed as a citizen science project with learning objectives as part of Citizen Cyberlab, as well as a technology platform for disaster response.

In GeoTag-X system design, data was collected in association with a particular project and analysed through modules associated with a project. A project was typically a disaster event, for example the 2013 Yamuna monsoonal floods, while a module was a type of analysis, for example geotagging or recording whether photos feature shelter. Modules built using HTML and Javascript were a series of analysis steps; the same code for modules could be applied in different projects. For example, the same code for geotagging photos in a project about a flood in India could be used for a project about landslides in Peru. Volunteers could codesign a module with a particular dataset in mind; media with which they frame their understanding of potential questions for analysis and develop shared understanding. One a module was published within a project category, volunteers could add more media to the initial dataset. The open nature of the module code as well as resulting data means that digital humanities researchers could explore values and assumptions embedded in the system, as well as resulting datasets.
A taxonomy of information management in disaster response (King 2005; Tatham and Spens 2011) was adapted for the GeoTag-X project in a project report (Cervigni and Smith 2014):

**Data**

A collection of related facts usually organized in a format such as a table or database and gathered for a particular purpose. In this sense, GeoTag-X produced image analyses as data tables associated with specific modules.

**Information**

Data that has been interpreted, verbalized, translated or transformed to reveal the underlying meaning or context. In this sense, the images shown on the GeoTag-X platform represented raw data, while volunteers’ image analyses created information that was saved as data tables.

**Knowledge**

Internalization of information, data and experience. In this sense GeoTag-X was a learning and training project building on data analyses. Knowledge can be further sub-divided into two categories:

1. **Tacit Knowledge**

   Personal knowledge resident within the mind, behavior and perceptions of individual members of the organization. Transforming the tacit knowledge of core project participants into explicit knowledge for sharing happened through project documentation.

2. **Explicit Knowledge**

   Formal, recorded or systematic knowledge that can easily be accessed transmitted or stored in computer files or hard copy. Explicit knowledge was what GeoTag-X aimed to generate for humanitarian disaster responses.

Research about citizen science and crowdsourcing indicates that volunteers should be able to usefully contribute limited time to a project, supported by results of usability studies (Jennet
and Cox (2014) which found that the GeoTag-X website, modules and tutorials needed to be as simple as possible to avoid people becoming frustrated and discontinuing analysis.

Steps within prototype learning modules were able to be categorised as one of three types: polar analyses, geotagging analyses or multiple choice analyses. However in all cases, even polar analyses, participants were given the option of choosing a “don’t know” option. The importance of actively labelling uncertainty was noted in a review of the accuracy of OpenStreetMap digital volunteers assessments of damage (Westrope et al. 2014). Types of analysis questions are explained from a technical perspective, followed by explanation of how each of the modules were developed from a participatory perspective.

**Binary or polar analyses**

Binary or polar analyses focused on yes or no, absent or present analyses. Volunteers were asked to consider a pair of alternatives and select which one to associate with the media being analyzed. However, all questions included a “don’t know” option, so participants could respond if they were not comfortable with the binary options. Below is an example of how a binary question was coded in Javascript in the system:

```javascript
{
  "question":"Can you see any water in the photo?",
  "key":"water",
  "type":"binary",
  "branch":{
    "no":"end" }
}
```

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1 Example from the project.json file available at: https://github.com/geotagx/geotagx-project-yamuna-floodwaters-2013/
The Javascript code above instructed the system to move on to another question if the participant answered no. If they answered yes, they were asked further questions about the water. If they responded saying they didn’t know, they were thanked for their time and given a new analysis task. Every module began with the polar analysis step of determining whether media is spam or not, so polar analyses were the base step for all modules.

**Geotagging analyses**

Another standard type of analysis is geotagging media on a map. Given the name and focus of GeoTag-X, geotagging analyses were core to the project. Below is an example of the typical code for geotagging tasks:

```javascript
{
    "question":"Can you geo-localize the photo?",
    "key": "latlancoords",
    "type": "geotagging"
}
```

Geotagging relied on OpenStreetMap instances embedded in the module. Users viewed an image on the right of the screen, then on the left of the screen either zoomed into a map area where they thought the image was located, or searched for a specific place name, which the map then displayed.

**Multiple-choice analyses**

Some modules contained multiple-choice steps asking volunteers to identify for example specific crops, animals, water or landscape features. An example of code for a single-answer
multiple choice question comes from a module analyzing agricultural crops in Somalia during drought².

```json
{
   "question":"Can you see the method of cultivation?",
   "key":"agCultivation",
   "type":"checklist",
   "parameters":{
      "options":[
         {
            "label":"Manual cultivation",
            "value":"Manual"
         },
         {
            "label":"With animals",
            "value":"Animals"
         },
         {
            "label":"By machine",
            "value":"Machine"
         }
      ]
   }
}
```

There were two types of multiple-choice analyses: single-answer and multiple-answer. These two sub-categories of multiple-choice are different both from technical and theoretical perspectives. These two types of multiple-choice categories lead to different answers in surveys and so cannot be assumed to be interchangeable in interpreting results.

Technically, single-answer analyses resulted in a single value associated with a media URL, while multiple-answer resulted in several new associated values. Single-answer values are studied in behavioural psychology and decision science because it means volunteers must make a forced choice, even if that choice is ‘don’t know’. Research suggests forced-choice

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² Example from the project.json file available at: https://github.com/geotagx/geotagx-project-somalia-crop-identification/
analyses encourages deeper processing of response options (Smyth et al. 2006). This is not practical however in situations where multiple choices are relevant data. Furthermore, displaying several valid values together as options may support learning in the form of pattern recognition, valuable if learning is an intended outcome.

For data verification, the PyBossa platform had a default value of 30 individual user analyses, given this value is commonly used for statistical analysis. It is this repeat analysis that makes PyBossa a crowdsourcing platform. Users (anonymous and authenticated) only participated once per analysis. After completing an analysis the system invited them to complete a different one. Developers could prioritize how the system would serve users new analyses. For example, a particular emergency response task could be prioritized to be presented to the next 30 users, quickly yielding a crowdsourced dataset. This might have potential ethical implications during simultaneous disasters and limited volunteer resources. So developers could alternatively prioritize a random task to be assigned to the next 30 users.

**Results**

Given that development of GeoTag-X was a research project, results were not only outputs as datasets but also development of the project modules themselves. Thus the development of question module types described in the method above were a project outcome. The outputs of modules were also results, as were their development. How modules were structured reflected technological limitations of the Pybossa open source code, as well as what kind of questions for analysis were valued.
Results were exportable as raw data in JSON or CSV format. A sample output of data from a single task in a module displayed in the format below, with identifying numbers replaced with x.

```json
{
    "info": {
        "isRelevant": "Yes",
        "latlan coords": "2.626953125, 41.7138671875",
        "img": "http://www.railnews.co.in/wp-content/uploads/2013/06/6171_3530_yamu.jpg",
        "task_id": 582
    },
    "user_id": xxxxx,
    "task_id": 582,
    "created": "2014-05-02T14:01:03.821552",
    "finish_time": "2014-05-02T14:01:03.821572",
    "calibration": null,
    "app_id": 27,
    "user_ip": xxxxx,
    "timeout": null,
    "id": 441
}
```

This example data output from a geotagging task is reproduced from Cervigni and Smith (2014, p31), in JSON format.

Analysis of data from authenticated users (Cervigni and Smith 2014, p35) showed that GeoTag-X reflected the norm of online communities in which a minority of participants engage heavily while the majority engage little (Wilkinson 2008). This was evidenced in the bounce rate showing that more than a third of users of the website simply visited the front page without contributing any analyses. Analysis in 2014 also showed that two-thirds of users...
Discussion

The *Digital Humanities Manifesto* (Schnapp and Presner 2009) promoted remixing, openness and the wisdom of the crowd (Spiro 2012, p22). The values of openness and crowdsourcing were reflected in the GeoTag-X project, nonetheless the idea of remixing was of concern to some in the disaster response community. Given that disaster response imagery can include sensitive data, there are risks that such data might be used inappropriately if analyses were invited from volunteers rather than experts. This risk was mitigated by the GeoTag-X system not storing imagery data or support uploading functions. Rather, the platform was designed to collate and analyze images already available via citizen or professional journalism online. This meant the GeoTag-X project itself was an example of remixing. GeoTag-X involved volunteers collating imagery about a particular disaster spread across the internet and collating it in a dataset for use in disaster response contexts. This was remixing news and social media content into a dataset for explicitly humanitarian aims.

The ethics of exposing volunteers to disaster response imagery was discussed in a 2014 workshop at the University of Vienna during a Science in Society Catalyst (SiS Catalyst) conference on science communication and social inclusion (Smith 2014). A primary discussion in this workshop was whether a ‘walled garden’ or closed platform should be developed, allowing staged levels of participation, in contrast to the entirely open platform in which users were randomly assigned tasks. A ‘walled garden’ would support for example restricting potentially gory disaster modules to people of a certain age. Debates about how
There was no consensus but rather active debate among the group of conference participants about whether a walled garden should replace the open platform. The current open platform stores media URLs from a range of online news sources that young people can access without restriction. The main argument against moving youth participation to a closed platform was that young people see these news stories and may face disasters in real life, so censoring this does not support their learning. Development of technologies like GeoTag-X could teach participants to view such media from a humanitarian perspective, rather than as a passive media consumer, which may have psychological and social benefits.

There was discussion about the potential for GeoTag-X to support learning about potential careers in humanitarian fields and how to respond to potentially distressing situations as a proactive and effective first responder. At the same conference Dawson (2012; 2014) experimented with GeoTag-X and shared perspectives about engaging with migrant communities to geotag content from their home countries. Considering impacts on volunteer users of the platform reflected the humanitarian context of the project.

The implications of different analysis types used in the project has been discussed. An untested type of analysis is one in which volunteers freely tag images with metadata of their choice. Researchers have suggested that allowing volunteers to freely tag images with metadata of their choice may be as productive for generating useful information as
developing prescribed modules. Stewart Buckfield, a creator of Flickr, one of the photo services used in GeoTag-X, discussed classification schemes:

“I think the lack of hierarchy, synonym control, and semantic precision are precisely why it works. Free typing loose associations is just a lot easier than making a decision about the degree of match to a predefined category (especially hierarchical ones). It’s like 90% of the value of a proper taxonomy but 10 times simpler” (Bishr & Kuhn 2007, p18).

Future research could explore information and learning outcomes comparing step-by-step analytical approaches used in GeoTag-X modules with free tagging of the same media. A hypothesis could be that modular analyses support greater learning, through volunteers questioning the reasons and values behind the programming of module steps. The challenges and extra effort involved in decisionmaking about predefined categories may be associated with more learning, in contrast with free tagging that may generate useful information, but without learning outcomes for those volunteering to crowdsource.

Imagery analysis differs from text analysis given linguistic barriers are removed. While text can be understood only by those people or machines literate in the given language, images can be interpreted by people from diverse cultural and linguistic backgrounds. Images do not need to be translated for different societies, though different people may consider different parts of an image significant. This diversity, while more challenging to manage within an information technology system, can also be a strength. The algorithms and machine interpretations built into any system design reflect certain values. Research has indicated that volunteer-based crowdsourced sentiment analysis is more accurate than an automatic sentiment analysis algorithm (Borromeo et al. 2015). Machine learning classifiers still need training for different events as well as validation (Palen et al. 2012; Cobb et al. 2013), so expectations of greater responsiveness or accuracy from machines alone may be unrealistic.
Designing a system for sharing information between organizations during complex and time-dependent disaster situations is challenging (Comfort & Zagorecki 2004; Kapucu 2006; Ren et al. 2008). Poor information sharing and coordination during disaster responses negatively impacts collective decision-making and resulting outcomes, including resource allocation, delayed evacuations and casualties (Bharosa et al. 2009). Crowdsourced media analyses will not solve these broader challenges. New challenges may be introduced; for example, researchers have called for more critical analysis of content emerging from social media in disaster situations given fake images may be shared (Gupta et al. 2013). Disaster responses remain challenging scenarios given timeframes, however crowdsourcing may alleviate some challenges in information sharing. Digital humanities research typically has longer time frames and less political pressure than disaster response work, so digital humanities researchers have opportunities to contribute to humanitarian work through engagement with open technology projects.
Conclusion

Digital humanities suggest not only the promise of collective intelligence but also collective intellect (Berry 2011, p2011). Values in the digital humanities include transparency and collaboration through online networks (Spiro 2012, p17). These values are compatible with explicitly humanitarian values, particularly given the emergence of open technology platforms driven by humanitarian organizations such as the UN. Open-source crowdsourcing platform Geotag-X engaged volunteers in analysing media about disasters, to contribute information and knowledge to disaster response agencies. Given the acute nature of disaster responses, digital humanities researchers may have more capacity to contribute to long-term projects for developing collective intellect than disaster response workers. Considering not only the datasets resulting from projects but also the questions embedded in the structures of crowdsourcing technologies could be a meaningful contribution of digital humanities researchers to humanitarian projects.
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