Visual Representations of Disaster

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ABSTRACT
Nepal was struck by two major earthquakes in April and May 2015 which gave rise to much media attention. Because of photographs' power to influence how people perceive significant events, we investigate how these disasters are represented visually through Twitter-shared images in three ways. First, we compare how geotagged image tweets are distributed vis-à-vis the reported damage, to see if a seemingly "objective" method of representation stands up. Second, with an iteratively developed coding scheme, we examine how images are differently produced and shared within global versus local populations and after each earthquake, with the idea that amplification "collectively instructs" what features of the event are most important. Third, we analyze how images from other locations, disasters, and time periods are appropriated as part of the "story" of the disaster event. We found differences in image popularity, with *global* twitterers emphasizing recovery and relief efforts in their diffusion of images, and *locals* emphasizing people suffering and major damage in their sourcing and re-sharing. We also found that *globals* were more likely to appropriate images, evoking lessons from Sontag about "the pain of others" [39].

AUTHOR KEYWORDS
Crisis Informatics; Geospatial Data; Photography; Social Computing

ACM Classification Keywords
H.5.3. Groups & Organization Interfaces—collaborative computing, computer-supported cooperative work; K.4.2. Social Issues

INTRODUCTION
The acceleration of image production and sharing in disaster response and its aftermath in a world now supported by social media begs to ask new questions about the representations of disaster through imagery. Sontag, in her essay *Regarding the Pain of Others*, explores the relationship between the subject of the photo, the photographer, its audiences, and the photo itself in relation to painful and traumatic events, cautioning that the power of the image lies not in helping us *remember* events, as many perceive, but rather *instructing us about what is important* to represent:

> *Strictly speaking, there is no such thing as collective memory—part of the same family of spurious notions as collective guilt. But there is* **collective instruction** *... What is called collective memory is not a remembering but a stipulating: that* this *is important, and* this *is the story about how it happened, with the pictures that lock the story in our minds.* Sontag [39, p. 85-86]

Imagery is so powerful that it skews stories toward the direction of the photographer but also in relation to its manner of distribution and extent of diffusion: what is seen influences how we are persuaded to come to understand what happened. With the rapid and frequent distribution of images through social media by multiple photographers, publishers, and republishers, the stories being told now about disasters are likely to multiply, but perhaps are different across populations of users.

In this paper, we examine the stories told through Twitter-diffused images of the earthquakes that struck Nepal in April and May 2015. We examine the question about how disasters are represented in three progressively probing ways. First, we examine the correlation between geotagged image tweets in the affected Nepali region and the distribution of structural damage to ask the straightforward question: how well does social media-distributed photography about damage represent the distribution of damage geographically? Are even these most distilled and "objective" measures of disasters' effects accurate?

Second, we investigate what images the Nepali population versus the rest of the world distributed: what were the most popular images of the event, and did they differ between those closer to the event linguistically and geographically, and those who were distant? Among which populations were these images diffused? This follows prior work that suggests that social media textual messages have different qualities and diffusion characteristics between local and global groups [22, 40, 42].

Third, we investigate the appropriation of imagery into the telling of the disaster event, and consider how, why, and by whom images that do not contain objective content about the disaster event become included.

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BACKGROUND

We review supporting literature in crisis informatics, human-centered computing, and social media image analysis to inform this research.

Crisis Informatics

Crisis informatics is the study of how people use digital technology to respond to disaster in creative ways to cope with uncertainty. Research in this area has exposed socio-behavioral phenomena such as the rise of digital volunteerism [41], the vocalization of personal experiences [3], and high tempo event reporting [20], and has informed improvements of response features including evacuation [18] and situational awareness [44] efficiencies.

In this paper, we are interested in a strand of crisis informatics that examines how social media users who are proximal to versus distant from a disaster event differently engage in social media activity, and in particular image-sharing. This is because, for some events, the whole world seems to respond online. Prior work indicates that social media interaction by people who are nearby a disaster event or who have close personal connections to the place (for example, property owners who live afar, or parents of children away at college) is different than those who are distant geographically and have few attachments to the place. Local and global users value different kinds of information, as seen through the retweeting practices during disaster events [40, 42]. Those close to the event versus those who are afar also propagate information differently, with locals favoring information from other locals [22]. In some cases, by isolating the affected population through a sequence of sampling methods to extract their social media data, we find that when their tweets are read as a lengthy monologue, the stories of their experiences are revealed. In examination of the Far Rockaway neighborhood in New York City, locals' social media narratives often revealed strong sentiments about being underserved by the government and underrepresented by the media in the aftermath of 2012's Hurricane Sandy [3]. We draw upon sampling and analytical methods from these studies to investigate the role of imagery in social media in the aftermath of disaster, and especially how imagery is produced and shared online by different populations.

Photos and Human-Centered Computing Research

HCI research has investigated the practices associated with photography with respect to the advent of photo sharing applications and pervasive cameras. At the individual level, research has examined motivations and intentions for photo-taking and -sharing [26, 45], which has informed the development of "photoware" [11]. Family groups display and share photos in their own interesting ways, and several studies have sought to design technology that support these group behaviors and practices [7, 10, 31, 32].

Social Media Image Analysis

With growth of social media, new practice-based and technical questions are being asked of photo- and other image-sharing, in part because it is so popular [44]. Social media posts containing images have been shown to receive higher user engagement on Twitter [34] and Facebook [35]. The rise of social media platforms dedicated to photo- and video-sharing demonstrates the compelling nature of visual imagery even in everyday communication [30]. Image-based communication can expose readers to other societies, geographies, ideas, and people, including both the photographer and the photographer's subjects. In addition, we know that during crisis events, people share and propagate images and video of impending hazards, of damage to critical infrastructure, of safety alerts and orders, and of lost people, pets, and important belongings [25, 48].

Motivating our first set of questions in this research concerning the relationship between geotagged imagery and damage, we surveyed prior work that has considered imagery and geospatial data together. Tools have been implemented to allow visualization of images from geotagged tweets on maps to learn about news and current events happening around the world [12, 49]. Abdullah et al. [2] combine methods in image processing, text processing, sentiment analysis, and data integration to infer societal happiness based on geotagged images shared on Twitter. Kawakubo and Yanai [19] extend an algorithm for ranking images based on similarity to incorporate images' geolocations. Geospatial metadata of photos have been used to automate generation of tourist maps and to detect events from distinct cameras [6, 8]. These ranging ideas about how geotagged images are used to different ends influenced our thinking about "representation."

The second part of our analysis involves finding the most popular images shared across different Twitter populations. Shamma et al. showed how feedback about group behavior on an online image-sharing platform aids editors in curating photos that meet their editorial requirements [37]. Often, analysis of images and their diffusion incorporates analysis of additional content types, such as machine-generated tags [13] and message source characteristics, e.g. social status of the user sharing content [44]. Defining and measuring popularity of images on social media are open research problems [5, 28]. Recent work on political identities on Instagram provided much insight on developing and applying an image coding scheme to social media image data [27]. Similarly, methods presented in [45] for categorizing and analyzing images of a crisis event based on visual content, as well as analyzing the diffusion of images based on sharing patterns, are particularly relevant to our study, both in domain and method.

Finally, informing the third part of our study, research on "citizen journalism" of disaster events [25] has motivated our work, including studies that have focused on the detection of false or appropriated images and rumors shared on social media, which creates a critical problem during disasters when people rely on accurate and timely information [4, 16, 29, 43].

THE 2015 NEPAL EARTHQUAKES

On April 25, 2015, a massive 7.8 earthquake struck Nepal with its epicenter east of the Gorkha district. Many large aftershocks continued over the following weeks causing more damage and distress, with people sleeping outside in case the aftershocks struck at night. A second 7.3 earthquake struck on May 12 near Mt. Everest. Even though these earthquakes struck less populous regions and caused less damage than predicted in a region that has been seismically staged for a major earthquake, these quakes were nevertheless some of the worst natural disasters to strike Nepal, killing over 8,000 people and destroying over 500,000 homes [15]. Nepal's economic loss has been reported at 10 billion U.S. dollars, or half of Nepal's gross domestic product [14].

DATA COLLECTION & ANALYTICS METHODS

Data Collection

We analyzed the images shared through Twitter in relation to these events because of access by a wide global audience. Starting on April 25, 2015, the day the first earthquake struck, we began collecting tweets on the event using our Project EPIC data collection infrastructure [3, 36]. The tweets were collected via Twitter's Streaming API based on a list of over 150 keywords that we deemed relevant based on manual inspection of tweets as the event unfolded (see Appendix). Note that tweets containing multi-language terms for "earthquake" are collected constantly as part of our lab's work, whereas terms particular to the Nepal earthquakes were launched as events unfolded throughout the first day. We collected data into 2016, ensuring that whatever temporal bounds were needed for analysis were possible.

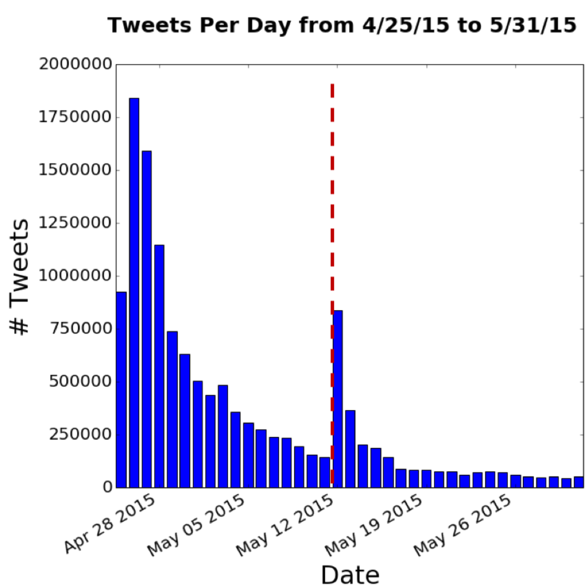

Figure 1. Number of tweets collected/day from April 25 to May 31, 2015. The dashed line falls just before the second earthquake, indicating the two data subsets.

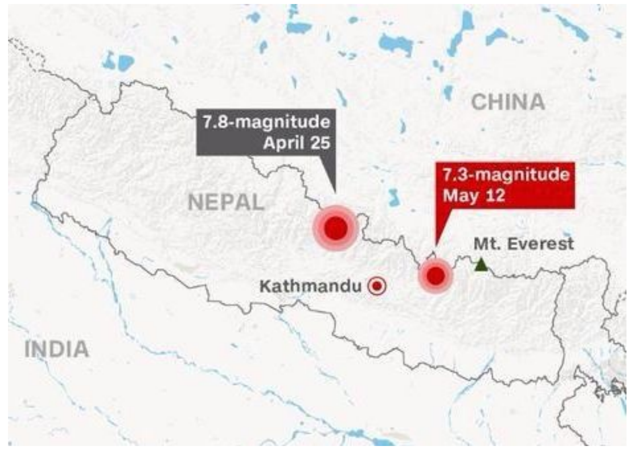

Figure 2. Epicenters of the 2015 earthquakes (CNN).

Figure 1 shows the number of tweets collected per day from April 25 through May 31, 2015, which in total number 12.9M. The first spike is on April 26, likely because the full data collection did not start until after the earthquake hit on the first day. The second spike on May 12 corresponds to the second major earthquake that occurred between the capital Kathmandu and Mt. Everest (see Figure 2).

We examined the data in two parts to correspond to each of the earthquakes: *after-first* (April 25–May 11, 2015) and *after-second* (May 12–May 31, 2015), indicated by the dashed line in Figure 1. This allows differences in image sharing and production after each earthquake, if any, to reveal themselves, especially since the first earthquake received more international coverage.

Additional Methods for Analysis Part 1: Structural Damage Correlation

Recall that we are analyzing Twitter images in three ways. For the first, to investigate the correlation between geotagged tweets in the Nepali region and the distribution of structural damage, we used damage assessment data from the National Geospatial-Intelligence Agency (NGA), specifically the NGA Nepal Earthquake Open Data Search application[1]. These data are derived from satellite imagery taken from April 26–May 13, 2015, which covers the immediate aftermath of both major earthquakes. Each data point has geographic coordinates, the recorded date, and classification as *Affected*, *Minor*, *Major*, or *Destroyed*. We also use population data from the 2011 Nepal census, taken at the district level[2]. We follow the methods described by Kryvasheyeu et al. [23] to calculate correlations between normalized tweet activity per capita and damage, and to measure rank correlation coefficients for affected districts.

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1 Data from Latest NGA Damage Assessment Points, http://nepal.nga.opendata.arcgis.com/datasets/5dd678370085409080c2c8f2ed019b55_0

2 Data from District/VDC wise population of Nepal (CBS 2011), http://umeshg.com.np/district-wise-population-of-nepal-cbs-2011/

Additional Methods for Analysis Part 2: Image Coding for Local and Global Twitter Populations

To learn about the representation of disaster via images, we are interested in analyzing the top images shared on Twitter in different populations. This involves finding all tweets with images, separating these images into groups based on the users' proximity to the disaster, finding the most retweeted images within each group, and then coding image tweets for content and intended meaning.

We filtered the 12.9M tweets for those containing an `entities.media.media_url` variable, which means they contain media uploaded through Twitter's image uploader, the only method to display media inline in a tweet. There were 3.7M such image-containing tweets (what we refer to as "image tweets"). A small portion (<1%) of these tweets contained non-photo content, i.e. videos or gifs, which we excluded. Tweets with links to articles which display a preview with an image were excluded from the set, as the metadata do not indicate which URLs produce such a preview. Image tweets that were no longer available on Twitter due to privacy settings, intentional deletion by the user, or inaccessible user accounts were also excluded from analysis.

To understand if and how people close to the event (*locals*) and people away from the event (*globals*) posted images, we divided the tweets into two broad analytical categories: (1) image tweets with associated text in Nepali and (2) image tweets with text in a language other than Nepali.

We consider the Nepali image tweets to represent the *local* population, or users who are likely to have close ties to Nepal. Our justification for using Nepali as a proxy for locality is that it is only spoken in Nepal as an official national language. Thus, we can make an informed assumption that people tweeting in Nepali are likely to have a significant connection to Nepal even if they do not reside there. (We use image tweets geotagged in Nepal as a proxy for locality only in the geospatial analysis—Part 1—as we found that the majority of these geotagged tweets are not posted by people who live in Nepal. Thus, we do not consider these tweets to be representative of the local population after comparing the data.) This leaves the non-Nepali tweets to represent the *global* public. Surely tweets coming out of Nepal also occurred in other languages, including English; we make a broad assumption that many such tweets are intended to communicate to a larger audience and therefore can stand in the *global* category, as opposed to tweets in Nepali which are clearly intended only for Nepali speakers. Though there are limitations with this approach, the geographical uniqueness of the Nepali language and the large number of tweets generated during this time period allow consideration of broad trends.

We first found the top retweeted images originally posted by *locals* and *globals* for each time range, *after-first* and *after-second*, resulting in four datasets total. We created MongoDB queries to find all retweets that fit the conditions of each category, then calculated aggregate values to count the occurrences of the retweets' `retweeted_status.id` (i.e., the tweet id of the originating tweet). Since this dataset comes from the Streaming API and does not include an entire history of Twitter data, it is not guaranteed that every original tweet for which there is a retweet exists in the dataset. Therefore, once we obtained the original tweet ids with the highest counts in each category, we then obtained the original tweet metadata by querying for a retweet of that tweet, since all retweets contain the full metadata for their originating tweet in the `retweeted_status` field. The counts of original image tweets for each category (and for image tweets geotagged in Nepal) are shown in Table 1.

	# of original image tweets	
Data subset	**4/25 - 5/11** (*after-first-earthquake*)	**5/12 - 5/31** (*after-second-earthquake*)
Not Nepali (*Global*)	509,102	134,598
Nepali *(Local)*	4,854	4,604
Geotagged in Nepal	884	402

Table 1. Originally-sourced image-containing tweet counts per data subset.

For each of the four datasets—*globally-sourced-after-first, globally-sourced-after-second, locally-sourced-after-first,* and *locally-sourced-after-second*—we hand-coded the Top 100 most retweeted image tweets, resulting in a full dataset of 400 image tweets. We chose the top retweets rather than using stratified samples because we are interested in what images were most likely to be seen on Twitter by users in each population group.

The coding scheme (Table 2) was developed iteratively, and then, once stable, was reapplied across all tweets. Emulating Mahoney et al. [27], we assigned one "primary" code to each image tweet based on what we deemed as both the primary focus of the image as well as the primary intent of the original sender for tweeting the image. For multi-photo tweets (tweets with 2-4 uploaded images), we similarly assigned one primary code for the tweet taking into consideration all of the attached images. (79 of the 400 tweets had multiple images). All Nepali language tweets were translated by a native speaker; languages that appeared in the global set were dominated by English; other non-English text was translated using Google Translate. *We used the tweet text to resolve meaning with respect to what the sender intended the meaning of the image to be*. We also used Google Image Search supplementally to find image source, when that was in question. Using one code per image tweet as the dominant message ensured accurate reporting of retweet counts per category. Example images for each coding scheme category are shown in Figure 3.

Code	Description
branded groups	Advertising or containing logos for organizations/companies.
celebrities	Featuring celebrities.
concern & prayer	Suggesting prayers or well-wishes, e.g. "Pray for Nepal."
missing & memorial	Missing people or people who died due to the earthquake.
non-photographic information	Text, documents, maps, infographics, or screenshots of social media/news. Not photos.
other	Apparently associated to the disaster or to Nepal (via data collection) not covered by the other categories.
people suffering	People who appear to be suffering from the earthquake in some way, injured, or dead.
politics & media	Political or mass media activity, or depicting opinions of such activity.
relief & recovery	Relief and recovery groups and their activity or proposed activity, e.g. supplies being distributed, people (civilians or responders) making assessments, teams/groups standing together, moving rubble, or designs for earthquake-resistant houses.
rescue	Rescue efforts in the immediate aftermath. This implies "people suffering" as well.
structural & environmental damage	Damage to buildings and infrastructure, or of natural disaster itself (e.g. landslide).

Table 2. Image tweet coding scheme.

To check for rating reliability, the two coders coded the same subset of 50 images. The inter-rater reliability, using two statistical measures, was: Fleiss' $\kappa = 0.889$ and Cohen's $\kappa = 0.923$, both of which indicate "almost perfect" agreement according to Landis and Koch [24]. We closely examined and discussed all conflicts, resolving those where possible. The primary coder coded the remaining dataset, with additional checks with the second coder along the way. This iterative process ensures that inter-rater reliability for the full dataset of 400 image tweets is higher than the initial inter-rater reliability test.

We coded as *other* any images that were apparently related either to Nepal or to the earthquake (such as images of Nepali cricket teams and politicians) based on their inclusion in our data collection. Even if the content of the image itself was not clearly related to the earthquake, we could not eliminate the possibility that users posted these images with Nepal recovery in mind. An example is an iconic photo of Mt. Everest, which could be a message of hope and recovery for Nepal, or could have had been a message of national pride that occurs also at other times.

On the other hand, we found some of the image tweets clearly irrelevant to the earthquake, despite being included in our collection. For instance, the keywords `landslide` and `avalanche` produced some noise, as they are terms used in many contexts (e.g. landslide victory, Avalanche hockey team). Once these noisy terms were identified via manual inspection, we excluded all image tweets that were collected only by these terms to be consistent.

Once we found the Top 100 tweets for each of the four datasets, we used a time zone approach to classify as *local* or *global* all retweets of these original tweets in our full collection, because most retweets do not have additional text associated with them to evaluate for language, and the retweeted tweet might be in a language that is not the user's own primary language. For each re-tweeter, we determined that they were *local* if their selected Twitter time zone was in the unique Kathmandu time zone, which covers all of Nepal, and which is 15 minutes off of countries surrounding it. A retweeter was otherwise considered *global*, unless their time zone was the default "None," in which case they were eliminated from this part of the analysis.

Additional Methods for Analysis Part 3: Image Appropriation

Third, we investigate the appropriation of imagery into the telling of the disaster event, and explore how, why, and by whom images that do not necessarily contain objective content about the disaster event are folded into the disaster account. For this analysis, we examined the images in each of the Top 100 image tweets in the *global* and *local* sets manually, using Google Image Search to find their origins. Each image was coded as being *of the time and place of this disaster*, *not in the time and place of the disaster,* or *ambiguous*. Four images from the full dataset of 400 image tweets were found to be appropriated, and one ambiguous.

ANALYSES & FINDINGS

Part 1: Structural Damage Correlation

We speculate that part of the representation of disaster stems from the relationship between where users tweet from and where the damage occurred. We map the tweets per capita using the 1,286 original tweets with images that are geotagged in Nepal in the full study time range, normalized by district-level population data (Figure 4). Figure 5 shows the distribution of NGA damage assessment points at the four damage levels in the affected districts.

We illustrate the correlations between damage and geotagged image tweet activity in Figure 6. Results are shown for cumulative damage, but were also calculated for each level of damage individually. The scatterplot indicates a positive correlation between damage and geotagged image tweet activity for all levels of damage based on the

Figure 3. Example images from each image tweet coding scheme category.

positive slope of the linear regression line. We found similar results for the three highest levels of damage (*Destroyed*, *Major*, and *Minor*), but a slightly negative correlation for *Affected* (likely because *Affected* points make up only 7% of the NGA dataset). Additionally, we calculated rank correlation coefficients—Kendall's τ, Spearman's ρ, and Pearson's ρ—between these variables and show results for cumulative damage in Table 3. All correlations are statistically significant with p-values <0.001, affirming a positive correlation between damage and geotagged image tweet activity in Nepal.

The linear-fit regression line (shown with a 95% confidence interval) makes clear the relationship between damage and tweet activity for each district. Those districts above the line experienced more damage than was represented by the number of images tweeted by users there—i.e., they were *underrepresented* on Twitter. Conversely, those districts below the line were *overrepresented* with respect to image tweets as compared to the amount of damage that occurred. Kathmandu, the most densely populated district, falls on or very near the line in all plots, showing that damage image tweets and amount of damage were closely correlated there.

However, the outliers suggest that one cannot reliably depend on this measure: Sindhupalchok and Nuwakot are the most underrepresented, and Rasuwa and Kaski the most overrepresented. In analyzing the image tweets geotagged in these districts, we find that the content of the images is largely *not* representative of damage. In Sindhupalchok, only 40% (n=66) of the image tweets were users' own photos of earthquake damage or aftermath; in Nuwakot, 22% (n=9); in Rasuwa, 17% (n=6); and in Kaski, 10% (n=122). Other images in these tweets include auto-generated maps and infographics alerting of recent earthquakes, news photos (which often portray locations other than where the tweets are geotagged), and other photos that may or may not be related to the earthquakes but do not portray damage. Although 68% of all users among the four districts could be determined to be individuals in Nepal, they produce only 37% of the tweets—the rest come from news reporting (or unidentifiable) accounts.

We speculate why these particular districts may be mis-represented; for instance, Kaski is the default geographic center of Nepal, so any tweets manually geotagged as "Nepal" will thus be geotagged specifically in Kaski. Sindhupalchok was the worst affected district, yet had relatively few geotagged image tweets. This district became hard to access due to damage and its already rural location; residents may not have been twitterers, and/or were not in a position to tweet following the earthquake. Outsiders who could have tweeted could not easily reach the area.

Part 2: Global vs. Local Representations

Qualitative analysis of the images uncovered differences in thematic image content propagated between the *local* and *global* populations and after the two separate earthquakes.

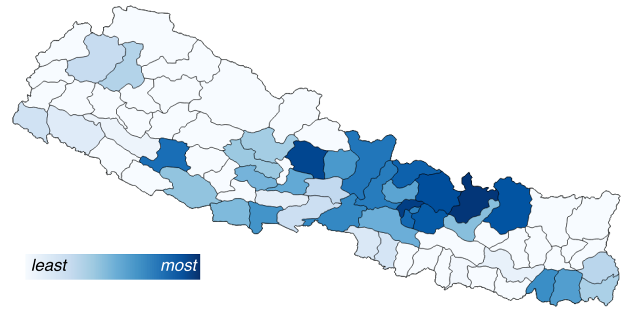

Figure 4. Tweets per capita based on original tweets with images that are geotagged in Nepal and district-level population data.

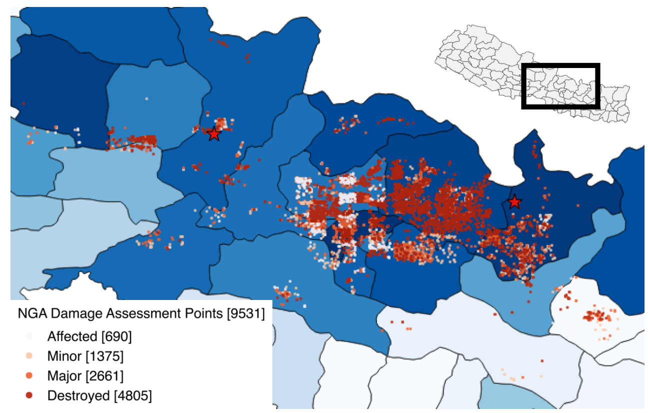

Figure 5. NGA damage assessment points overlayed on map depicting tweets (geotagged with images) per capita. Numbers in brackets represent total number of points in each category.

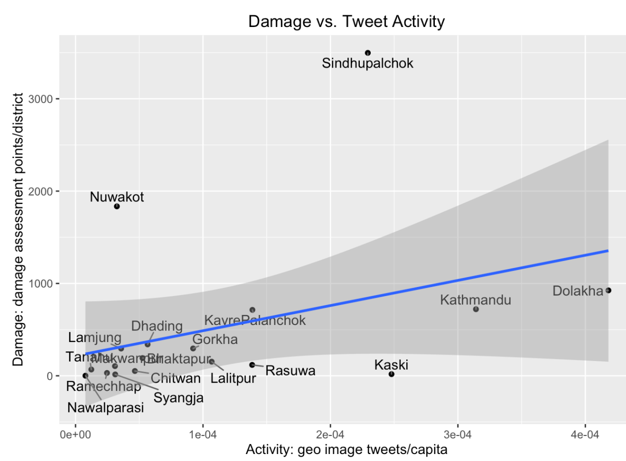

Figure 6. Plot of geotagged image tweet activity in the full study date range *v* damage, which is measured in no. of NGA damage assessment points at all levels/district. The best-fit regression line shows a positive correlation.

	Statistic
Kendall's τ	0.53 ($p < 0.001$)
Spearman's ρ	0.62 ($p < 0.001$)
Pearson's ρ	0.50 ($p < 0.001$)

Table 3. Rank correlation coefficients for all damage compared to geotagged image tweet activity.

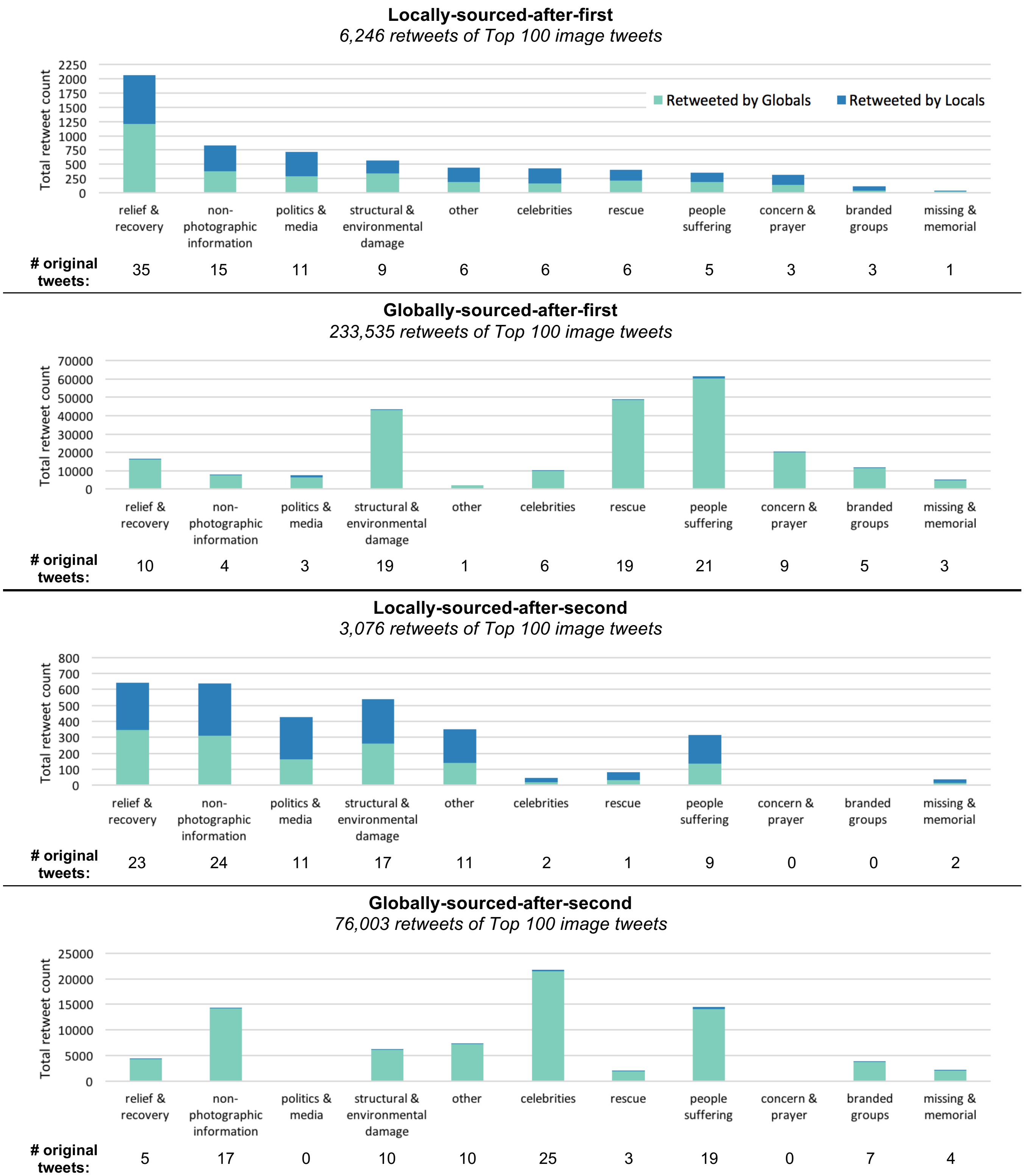

Figure 7. Distribution of retweets of each image category for each dataset. Also shown is the split between retweets by *locals* and by *globals*. The numbers beneath each category are the number of original images (out of the Top 100) for that category. All charts are sorted according to locally-sourced-after-first original image tweet popularity. Globally-sourced image tweets are retweeted almost exclusively by *globals*, whereas locally-sourced tweets are more frequently retweeted by *locals*.
(Note different y-axis scales.)

The distribution of thematic image categories for retweets of each of the four sets of original image tweets based on coding are shown in Figure 7. A chi-square test shows that the differences in coding between the four subsets are statistically significant, $\chi^2(24, N=400) = 147.87$, $p<.001$. Recall that our interest here is how the propagation of images indicates what Sontag refers to as "collective instruction" about what populations deem important to stipulate about the impact of an event.

In the aftermath of the first earthquake, the differences in the Top 100 datasets between the *local* and *global* populations are substantial. Whereas the most popular (via retweet) images (considering here both original image and retweet image rates combined) in the *local* group are on *relief & recovery*, *non-photographic information* (like maps and charts), and *politics & media*, these categories are among the least popular in the *global* user population. Rather, in the *globally-sourced-after-first* set, images of *people suffering* as well as images of *rescue* (which, by their nature, also portray people suffering) were the most tweeted, followed by images of *structural & environmental damage*. This suggests that the *global* population is captivated by emotionally compelling pictures of the disaster while *locals* focus on other matters, perhaps for a variety of reasons, including that propagating *people suffering* and *rescue* could over-represent the lived experience and/or that *locals* are looking for information that allows them to act by helping others or themselves.

After the second earthquake, we see images of *celebrities* being retweeted frequently only in *globally-sourced-after-second*. These images were comparatively retweeted very infrequently in the other three datasets. Images in the *non-photographic information* category were also common in the *locally-sourced-after-second* dataset. This category includes images of long sections of text on topics such as assessing earthquake damage and infographics of earthquake effects; many of these images are presumably meaningful primarily to locally affected people.

Retweet counts were much higher after the first earthquake relatively across both sets, and for globally-sourced image tweets across both earthquakes: *locally-sourced-after-first* image tweets were retweeted 6K times, *globally-sourced-after-first* 233K, *locally-sourced-after-second* 3K, and *globally-sourced-after-second* 76K times. Regarding retweeting behavior, we see that in general, image tweets from *globals* are retweeted almost exclusively by *globals*, whereas image tweets from *locals* have a much higher rate of *local* retweeting. Specifically, we see *locals* retweet other *locals' non-photographic information* and *politics & media* imagery the most, as these are particularly relevant to *locals* and irrelevant or even incomprehensible to *globals*. However, the *local* image tweets in other categories are also highly retweeted by *globals*, indicating that *globals* find value in locally sourced imagery and play a role in diffusing and amplifying local representations of the disaster. In other words, the *global* audience in part *derives* its material from the local, *generative* audience [42]. The data also show a notable disappearance of *concern & prayer* imagery during *after-second*, indicating that the event lost attention from all populations as time passed after the initial earthquake.

For *locals*, images in the same categories (*recovery & relief*, *non-photographic information*, and *politics & media*) remained the most shared and retweeted after each earthquake, with *structural & environmental damage* also rising as a top category. For *globals*, though, we see a shift in image content between the two events—particularly from *people suffering* as the clear top category to *celebrities*. Though images of *people suffering* and *damage* are still popular among *globals* in *after-second*, retweets of *celebrities* in the Top 100 outstrip retweets of any other image category.

Part 3: Appropriation of Imagery

We investigate the appropriation of photos taken outside the time and space of the disaster events into the story of the April and May earthquakes, examining any differences there might be between the *local* and *global* data sets. Overall, we found four images in the full dataset of 400 image tweets that were confirmed to be appropriated from other times and/or places in *globally-sourced-after-first*, and an additional image in *locally-sourced-after-first* that has ambiguous origins. No indications of appropriated imagery were found in the other datasets.

The second most retweeted image overall is of a young boy said to be holding his younger sister (Figure 8). Most of the retweets of this image are a cropped version of Figure 8 and say that it is a "young boy protecting his sister in Nepal." This image is in fact not related to the Nepal earthquake at all—and on May 2, 2015, as a result of this incorrect rumor, the photographer tweeted the original, uncropped version of this image showing the copyright watermark to say:

Figure 8. Photo of children in Vietnam in 2007, but rumored to be taken in Nepal earthquake aftermath. ©nason-nguyen

```
This is my photo about two Vietnamese
Hmong ethnic children taken in 2007 in
Ha Giang province, it's not about Nepal.
(@nasonnguyen)
```

In interviews, he explains how this is not the first time this image has been appropriated. In this case, the image was resurfaced after the earthquake and made to appear to depict two lonely, scared children [33]. It appears in this appropriated form eight times in *globally-sourced-after-first* (not including the photographer's tweet), accounting for 38% of all original image tweets in the *people suffering* category for this dataset. (Note that to keep to a consistent rule, similar images were not collapsed together into one in the Top 100 datasets, because sometimes images were taken from a similar vantage point, or were in yet another way very slightly different—cropped or otherwise edited—making it sometimes difficult to determine uniqueness.)

Another top retweeted image in the *globally-sourced-after-first* set, retweeted over 1,500 times, shows an impressive scene of thousands of monks praying together in formation (Figure 9). According to the post by an American news writer on April 25, the image shows 100,000 monks praying after the earthquake as "a necessary gesture of power." However, numerous comments on the tweet, including one by the original twitterer, reveal that this photograph was taken in Thailand in 2010 [21]. The original twitterer himself said:

```
Yes, I know this photo by Luke Duggleby
is a couple years old, but it still
speaks a powerful message for right now.
#NepalEarthquake. (@tsbugg)
```

There were two instances of damage photos from other earthquakes folded into multi-photo tweets in which the rest of the photos were from the Nepal earthquake (Figure 10). One (from @The_Onliest_) shows a shattered road taken after the 2013 Bohol earthquake in the Philippines, and the other (from @MrAlMubarak) shows damaged buildings after the 2008 Sichuan earthquake in China. The tweet containing the first image has replies from users who are skeptical of its origins, while the tweet containing the second contains no indication that it depicts a different earthquake, but we ourselves suspected a mismatch. Further investigation into both photos revealed occurrences on blogs and news articles dated before the Nepal earthquake, confirming their origins from other events.

Finally, a dramatic image of birds sitting atop wood debris (Figure 11) was shared by local user @chandangoopta in a Nepali tweet about hope in recovery, and includes #NepalQuake," implying that this image shows damage from the earthquake. As with the previous examples, tweet replies point to its ambiguous origins, as the original twitterer says that he has "no idea" to whom to credit the photo, with different answers from others that we could not substantiate as being from the time and place of the earthquakes.

Figure 9. The original tweet (from @tsbugg) claimed these were praying monks after the Nepal earthquake; the photo was in fact taken in Thailand in 2010.

Figure 10. Two images of damage made to appear to be the aftermath of the Nepal earthquake. They are rather aftermath photos of earthquakes in 2013 in the Philippines (top, from @The_Onliest_) and in 2008 in China (bottom, from @MrAlMubarak).

Figure 11. Image of ambiguous origins showing birds atop timber (from @chandangoopta).

Common in all these examples is a sense of drama—children suffering, monks praying, extensive damage, a flock of black birds. That four of the five images are confirmed as appropriated from other events, yet were among the most retweeted images from this event, shows how compelling images gain popularity online, especially from the global population.

We note that, though in some cases, there is no indication that the imagery depicts something other than the Nepal earthquake, in others we located users who initially tweeted these images acknowledging the appropriation (or lack of proper attribution). Some users may tweet appropriated imagery as an honest mistake, as it can be difficult to determine whether an image is from a different time, place, and/or event. For others, the open acknowledgment suggests that they do not perceive appropriation as a malicious practice in this context. Rather, for them, it seems to be another way of visually representing disaster and garnering support through compelling imagery. However, we know, too, that the public challenges to the photos' origins, and the photographers' responses, indicate that the appropriation into the Nepal disaster story is still questionable to some.

DISCUSSION

These investigations reveal that there are multiple stories being told, even at a macro scale of analysis that treats popular diffusion of images (the Top 100) as the singular point of view. Of course, any viewership will construct its own story, but even that is derived from much of the same material from which many other stories are told. In addition, we know that there are multiple intentions at work: that of the photographer, perhaps that of the subject of the photo, that of the social media sender, those of the re-senders, and even those of the researchers, who try to "categorize" content based on its seemingly salient features.

When we examine the results of Part 1—the correlations between the geotagged image tweets and the distribution of damage across the region—we learn that, in aggregate, they correlate closely. What does this reveal, and what mistakes would a "researcher's intention" make by leaving the analysis there? Statistically, the relationship is in some places significant. Some data science projects would be satisfied with the result that the occurrence of geotagged tweets is correlated to the amount of damage. Examination of the images however, and of the twitterers who produce them, paints a different picture: the images are less frequently photos of on-the-ground activity, and more frequently infographics and maps that originate from news and media accounts that are not mobile—in other words, their geotags mean relatively little in relation to the finer aspects of geography and damage in Nepal. What we learn, in short, is that geotagged images coming from Twitter are *not* representative of the Nepal disaster in terms of "objective" depictions of damage, even though there just happens to be a good enough geographical correlation.

When we examine in Part 2 what we call *local* and *global* populations, using Nepali language as the "language-world" proxy for *locally-sourced* tweets, even with all the limitations that that introduces, differences start coming into view, indicating the topics that Nepali speakers are most concerned about and what the rest of the world is most concerned about are different. Retweeting *locals* focus more on *relief and recovery* imagery, *non-photographic information* (like maps and infographics) and *structural damage* imagery more than the retweeting *globals* do, whereas *globals* focus more on *people suffering* and *rescue* activities. This finding is consistent with other social media research that indicates that people close to the event look for particulars that might help them understand the extent of the destruction [22, 40, 42]. The retweeting *globals* care more about the abstract of the event, and perhaps the dramatic retelling of it: they need not, for example, go to work in the region of the disaster, nor find out what buildings are safe to continue with their lives. Furthermore, we learn that global retweeters rely on content produced by local sourcers, and that, in terms of their retweeting characteristics, locals pursue content from other locals.

Part 3 makes this point even clearer, with four photos—and one occurring eight times by different senders—in the *globally-sourced* Top 100 that are confirmed to be appropriated from other times and places to become a part of the Nepal earthquake disaster account. The number of images is not large, but their re-distribution is, and communicates much more drama in relation to how *locals* perceive the event.

The inquiry aligns closely with Sontag's treatment of photography [38], and particularly photography that captures the "pain of others" to use her words [39]. Sontag, reflecting on the depiction of war, explains that:

> *Awareness of the suffering that accumulates in a select number of wars happening elsewhere is something constructed. Principally in the form that is registered by cameras, it flares up, is shared by many people, and fades from view. In contrast to a written account—which, depending on its complexity of thought, reference, and vocabulary, is pitched at a larger or smaller readership—a photograph has only one language and is destined potentially for all.* [39, p. 20]

The "one language" of photos is what makes them so powerful and allows different kinds of meaning to be attached with text; even a "#nepal" is what makes them malleable to the assumption of different intents, often different than the photographer's intent. That there are differences in the *local* and *global* populations' popularity of images indicates that we can infer what the observer of the image at least partially intends: that is, to observe and understand the event through the pain of others. Even the photo of the Vietnamese children has much meaning placed upon it: they are neither victims of the earthquake nor Nepali, and they may not even be desperately unhappy.

They could instead be in a state of play, with one consoling the other because an action on the playground was misunderstood. They may not be "people suffering," but the associated tweet text indicates that the sender thinks this, and indeed "instructs," to borrow again from Sontag, that the audience see the image in this way as well.

This begs the question of *what is the goal of the watcher* in these events that can now easily be photographically shared rapidly and frequently. To what extent do we see people outside the area of affect as "curious onlookers," or even the more distasteful "disaster tourists" [9, 17]? To what extent is watching required to be an informed citizen to know what is happening *and* that it happened, and how do we—or even *can* we—separate that obligation from the "pleasure of flinching" [39, p. 41]? There are allegedly those who deny the horrors of Nazi Germany; therefore, to watch is to witness. It is a responsibility to watch, even when watching is nevertheless entangled with problems of objectification and gratitude for not being a victim oneself.

Two Competing Expectations: Journalistic Accuracy and Drawing a Collective Gaze

These issues have always been entangled with photography—both the viewing of and the taking of—but social media brings these complications into a new light.

Specifically, we see that there are competing expectations with viewing imagery as distributed through social media. One of the expectations that comes with use of many social media platforms—and certainly Twitter—is the "real-time" quality of them. To tweet is to say what is happening "right now" or very recently, or at least that is the expectation of many. Associated images then, are assigned that same expectation—a *journalistic accounting* of what is happening on the ground. In this expectation trajectory, to watch is to be accurately informed.

However, another consequence of social media is social connection, sometimes to people far and wide. The sharing of images here might have different goals, including that of collective watching and developing widely shared intersubjective knowledge of the event, and fostering feelings of solidarity with those suffering. The preponderance of images of people suffering and being rescued, then, is designed to *compel a collective gaze* to be drawn to the event. It is a curious thing when significant disasters happen and the world's gaze cannot be drawn, and perhaps is even studiously averted. Are the events not photographable enough? Indeed, in this research the data after the second earthquake suggest that the *global* population needs new techniques for maintaining its gaze as attention to the shocking first earthquake wanes: we see the rise of celebrity-associated messaging.

The appropriation of imagery to attract the world's gaze, then, might have inherent problems with misuse of copyright, for example, but the intention of the appropriator will be different depending on what expectation is placed upon the act. To assume journalistic accuracy of appropriated images is a violation of the first expectation, but perhaps not the second, which emphasizes persuasion for collective emoting. The photographs might even be "stand ins" for the real thing that could not otherwise be photographed. Surely children were scared. Surely religious people prayed, so why not borrow photos to be used symbolically? Further still, maybe the intention of the photo of the monks was not to represent something happening *in* Nepal, but instead shared to say "the world cares," or more specifically, "Thailand cares." But of course the watcher may read and amplify the message for a different intention: such is the conflict between the two competing expectations of imagery, especially when diffused over social media.[3]

Though the relationships between posters and audiences are muddied by these different purposes as they propagate over time, the sourcing and amplifying audience of the *globals* appears to favor those images that display hardship and victimhood, whereas *locals* favor substantive information upon which they can perhaps act. The audiences themselves iteratively sort the messages for subsequent consumption.

CONCLUSION

We have investigated the representation of the 2015 Nepal earthquakes via images shared on Twitter, attending to the lessons of Sontag [39], and the role that imagery plays in the dynamics of relating to the pain of others. We found that though the location of geotagged tweets correlates to the distribution of damage by districts, content analysis shows little connection. An analysis of the Top 100 image tweets in the *local* and *global* populations, using Nepali language tweets as a proxy for locality, show a different diffusion of content, with *locals* focusing more on the business of the response and the damage the earthquake caused in their cities. The *global* population focused more on the images of people suffering. After the second earthquake, the results shift for *globals* but less for *locals*, suggesting some disaster fatigue for those not affected by the events. The attention of celebrities gains ground after the second earthquake for the *globals*, suggesting the need for new mechanisms for maintaining the world's gaze upon Nepal. Appropriation of imagery not of the Nepal earthquake has purposes that violate one expectation—that of journalistic accuracy—but honor another—that of drawing a collective gaze onto a disaster scene.

[3] The competing expectations are brought deeper into battle when an appropriated image is included in a collage of images that are journalistically accurate. The sender's work in such cases might be indicative of sloppy journalism (when three images about damage come from Nepal but a fourth about damage does not); or of emotional instruction or even manipulation (when images of damage are accompanied by the photo of young Vietnamese children); or even still of perhaps education (when images of damage are accompanied by an image of Mt. Everest, subtly locating the general region of affect).

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REFERENCES
1. Saeed Abdullah, Elizabeth L. Murnane, Jean M.R. Costa, and Tanzeem Choudhury. 2015. Collective Smile: Measuring Societal Happiness from Geolocated Images. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing - CSCW '15*, ACM Press, 361–374. DOI: http://doi.org/10.1145/2675133.2675186
2. Jennings Anderson, Marina Kogan, Melissa Bica, Leysia Palen, Kenneth Anderson, Kevin Stowe, Rebecca Morss, Julie Demuth, Heather Lazrus, Olga Wilhelmi, and Jennifer Henderson. 2016. Far Far Away in Far Rockaway: Responses to Risks and Impacts during Hurricane Sandy through First-Person Social Media Narratives. In *Proceedings of the 13th International Conference on Information Systems for Crisis Response and Management* (ISCRAM '16).
3. Kenneth M. Anderson and Aaron Schram. 2011. Design and implementation of a data analytics infrastructure in support of crisis informatics research (NIER track). In *Proceedings of the 33rd International Conference on Software Engineering* (ICSE '11). ACM, New York, NY, USA, 844-847. DOI: http://dx.doi.org/10.1145/1985793.1985920
4. Christina Boididou, Symeon Papadopoulos, Yiannis Kompatsiaris, Steve Schifferes, and Nic Newman. 2014. Challenges of computational verification in social multimedia. In *Proceedings of the companion publication of the 23rd international conference on World wide web companion*. International World Wide Web Conferences Steering Committee, 743–748.
5. Spencer Cappallo, Thomas Mensink, and Cees G.M. Snoek. 2015. Latent Factors of Visual Popularity Prediction. In *Proceedings of the 5th ACM on International Conference on Multimedia Retrieval* (ICMR '15). ACM Press, New York, New York, USA, 195–202. DOI: http://dx.doi.org/10.1145/2671188.2749405
6. Wei-Chao Chen, Agathe Battestini, Natasha Gelfand, and Vidya Setlur. 2009. Visual summaries of popular landmarks from community photo collections. In *Proceedings of the Seventeenth ACM International Conference on Multimedia* (MM '09). ACM Press, New York, New York, USA, 789. DOI: http://dx.doi.org/10.1145/1631272.1631415
7. Andy Crabtree, Tom Rodden, and John Mariani. 2004. Collaborating around Collections: Informing the Continued Development of Photoware. In *Proceedings of the 2004 ACM Conference on Computer Supported Cooperative Work* (CSCW '04). ACM Press, New York, New York, USA, 396. DOI: http://dx.doi.org/10.1145/1031607.1031673
8. Hugo Feitosa de Figueirêdo, João Paulo Ribeiro da Silva, Daniel Farias Batista Leite, and Cláudio de Souza Baptista. 2012. Detection of photos from the same event captured by distinct cameras. In *Proceedings of the 18th Brazilian symposium on Multimedia and the web* (WebMedia '12). ACM Press, New York, New York, USA, 51. DOI: http://dx.doi.org/10.1145/2382636.2382650
9. Alexander de Waal. 1997. *Famine Crimes: Politics & the Disaster Relief Industry in Africa*. Indiana University Press.
10. Abigail Durrant, Alex S. Taylor, David Frohlich, Abigail Sellen, and David Uzzell. 2009. Photo displays and intergenerational relationships in the family home. In *Proceedings of the 23rd British HCI Group Annual Conference on People and Computers: Celebrating People and Technology.* British Computer Society, 10–19. DOI: http://dl.acm.org/citation.cfm?id=1671011.1671013
11. David Frohlich, Allan Kuchinsky, Celine Pering, Abbe Don, and Steven Ariss. 2002. Requirements for photoware. In *Proceedings of the 2002 ACM Conference on Computer Supported Cooperative Work* (CSCW '02). 2002. DOI: http://dl.acm.org/citation.cfm?id=587102
12. Brendan C. Fruin, Hanan Samet, and Jagan Sankaranarayanan. 2012. TweetPhoto: photos from news tweets. In *Proceedings of the 20th International Conference on Advances in Geographic Information Systems* (SIGSPATIAL '12). ACM Press, New York, New York, USA, 582. DOI: http://dx.doi.org/10.1145/2424321.2424421
13. Venkata Rama Kiran Garimella, Abdulrahman Alfayad, and Ingmar Weber. 2016. Social Media Image Analysis for Public Health. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (CHI '16). ACM Press, New York, New York, USA, 5543–5547. DOI: http://dx.doi.org/10.1145/2858036.2858234
14. Katsuichiro Goda, Takashi Kiyota, Rama Mohan Pokhrel, Gabriele Chiaro, Toshihiko Katagiri, Keshab Sharma, and Sean Wilkinson. 2015. The 2015 Gorkha Nepal Earthquake: insights from earthquake damage survey. *Frontiers in Built Environment* (2015). DOI: http://dx.doi.org/10.3389/fbuil.2015.00008
15. Government of Nepal. 2015. Nepal Earthquake 2015: Post Disaster Needs Assessment Executive Summary.
16. Aditi Gupta, Hemank Lamba, Ponnurangam Kumaraguru, and Anupam Joshi. 2013. Faking Sandy: characterizing and identifying fake images on Twitter during Hurricane Sandy. In *Proceedings of the 22nd*

international conference on World Wide Web companion. International World Wide Web Conferences Steering Committee, 729–736.

17. Amanda L Hughes, Leysia Palen, Jeannette Sutton, Sophia B Liu, and Sarah Vieweg. 2008. Site-Seeing in Disaster: An Examination of On-Line Social Convergence. In *Proceedings of the 5th International Conference on Information Systems for Crisis Response and Management* (ISCRAM ‘08). 324–333.
18. Isabel Shizu Miyamae Iwanaga, The-Minh Nguyen, Takahiro Kawamura, Hiroyuki Nakagawa, Yasuyuki Tahara, and Akihiko Ohsuga. 2011. Building an earthquake evacuation ontology from twitter. In *2011 IEEE International Conference on Granular Computing*. IEEE, 306–311. DOI: http://dx.doi.org/10.1109/GRC.2011.6122613
19. Hidetoshi Kawakubo and Keiji Yanai. 2011. GeoVisualRank: A Ranking Method of Geotagged Images Considering Visual Similarity and Geo-location Proximity. In *Proceedings of the 20th international conference companion on World wide web* (WWW ’11). ACM Press, New York, New York, USA, 69. DOI: http://dx.doi.org/10.1145/1963192.1963228
20. Brian Keegan, Darren Gergle, and Noshir Contractor. 2012. Staying in the loop: structure and dynamics of Wikipedia’s breaking news collaborations. *Proceedings of the Eighth Annual International Symposium on Wikis and Open Collaboration*. http://dl.acm.org/citation.cfm?id=2462934
21. Kelley King. 2015. Luke Duggleby: Monks in Prayer and the Power of Social Media. (June 1, 2015). Retrieved May 20, 2016 from https://wonderfulmachine.com/blog/luke-duggleby-monks-and-the-power-of-social-media
22. Marina Kogan, Leysia Palen, and Kenneth M. Anderson. 2015. Think Local, Retweet Global: Retweeting by the Geographically-Vulnerable during Hurricane Sandy. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing* (CSCW ’15). ACM Press, Vancouver, 981–993. DOI: http://dx.doi.org/10.1145/2675133.2675218
23. Yury Kryvasheyeu, Haohui Chen, Nick Obradovich, Esteban Moro, Pascal Van Hentenryck, James Fowler, and Manuel Cebrian. 2016. Rapid assessment of disaster damage using social media activity. *Science Advances* 2, 3 (Mar 2016), e1500779–e1500779. DOI: http://dx.doi.org/10.1126/sciadv.1500779
24. J. Richard Landis and Gary G. Koch. 1977. The Measurement of Observer Agreement for Categorical Data. *Biometrics* 33, 1 (Mar 1977), 159. DOI: http://dx.doi.org/10.2307/2529310
25. Sophia B. Liu, Leysia Palen, Jeannette Sutton, Amanda L. Hughes, and Sarah Vieweg. 2008. In Search of the Bigger Picture: The Emergent Role of On-Line Photo Sharing in Times of Disaster. In *Proceedings of the 5th International Conference on Information Systems for Crisis Response and Management* (ISCRAM ‘08).
26. Mathias Lux, Marian Kogler, and Manfred del Fabro. 2010. Why Did You Take this Photo? A Study on User Intentions in Digital Photo Productions. In *Proceedings of the 2010 ACM workshop on Social, adaptive and personalized multimedia interaction and access* (SAPMIA ’10). ACM Press, New York, New York, USA, 41. DOI: http://dx.doi.org/10.1145/1878061.1878075
27. Jamie Mahoney, Tom Feltwell, Obinna Ajuruchi, and Shaun Lawson. 2016. Constructing the Visual Online Political Self: An Analysis of Instagram Use by the Scottish Electorate. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (CHI ’16). ACM Press, New York, New York, USA, 3339–3351. DOI: http://dx.doi.org/10.1145/2858036.2858160
28. Philip J. McParlane, Yashar Moshfeghi, and Joemon M. Jose. 2014. “Nobody comes here anymore, it’s too crowded”; Predicting Image Popularity on Flickr. In *Proceedings of International Conference on Multimedia Retrieval* (ICMR ’14). ACM Press, New York, New York, USA, 385–391. DOI: http://dx.doi.org/10.1145/2578726.2578776
29. Marcelo Mendoza, Barbara Poblete, and Carlos Castillo. 2010. Twitter under crisis: can we trust what we RT?. In *Proceedings of the First Workshop on Social Media Analytics* (SOMA ’10). ACM Press, New York, New York, USA, 71–79. DOI: http://dx.doi.org/10.1145/1964858.1964869
30. Oded Nov, Mor Naaman, and Chen Ye. 2009. Analysis of participation in an online photo-sharing community: A multidimensional perspective. *Journal of the American Society for Information Science and Technology* 61, 3: 555–566.
31. Michael Nunes, Saul Greenberg, and Carman Neustaedter. 2008. Sharing digital photographs in the home through physical mementos, souvenirs, and keepsakes. In *Proceedings of the 7th ACM conference on Designing interactive systems* (DIS ’08). ACM Press, New York, New York, USA, 250–260. DOI: http://dx.doi.org/10.1145/1394445.1394472
32. Daniela Petrelli, Simon Bowen, and Steve Whittaker. 2014. Photo mementos: Designing digital media to represent ourselves at home. *International Journal of Human Computer Studies* 72, 3 (Mar 2014), 320–336. DOI: http://dx.doi.org/10.1016/j.ijhcs.2013.09.009
33. Nga Pham. 2015. Haunting ‘Nepal quake victims’ photo from Vietnam. (May 4, 2015). Retrieved April 30, 2016 from http://www.bbc.com/news/world-asia-32579598

34. Simon Rogers. 2014. What fuels a Tweet's engagement? (March 10, 2014). Retrieved May 24, 2016 from https://blog.twitter.com/2014/what-fuels-a-tweets-engagement
35. Gregory D Saxton and Richard D Waters. 2014. What do Stakeholders Like on Facebook? Examining Public Reactions to Nonprofit Organizations' Informational, Promotional, and Community-Building Messages. *Journal of Public Relations Research* 26, 3 (2014), 280–299. DOI: http://dx.doi.org/10.1080/1062726X.2014.908721
36. Aaron Schram and Kenneth M. Anderson. 2012. MySQL to NoSQL: data modeling challenges in supporting scalability. In *Proceedings of the 3rd annual conference on Systems, programming, and applications: software for humanity* (SPLASH '12). ACM, New York, NY, USA, 191-202. DOI: http://dx.doi.org/10.1145/2384716.2384773
37. David A Shamma, Lyndon Kennedy, Jia Li, Bart Thomee, Haojian Jin, and Jeff Yuan. 2016. Finding Weather Photos: Community-Supervised Methods for Editorial Curation of Online Sources. *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing* (CSCW '16). ACM Press, 86–96. DOI: http://doi.org/10.1145/2818048.2819989
38. Susan Sontag. 1977. *On photography*. Macmillan.
39. Susan Sontag. 2003. *Regarding the pain of others*. Presses Universitaires de France.
40. Kate Starbird and Leysia Palen. 2010. Pass It On?: Retweeting in Mass Emergency. In *Proceedings of the 7th International Conference on Information Systems for Crisis Response and Management* (ISCRAM '10).
41. Kate Starbird and Leysia Palen. 2011. "Voluntweeters": Self-organizing by Digital Volunteers in Times of Crisis. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (CHI '11). ACM, New York, NY, USA, 1071–1080. DOI: http://dx.doi.org/10.1145/1978942.1979102
42. Kate Starbird, Leysia Palen, Amanda L. Hughes, and Sarah Vieweg. 2010. Chatter on the Red: What Hazards Threat Reveals About the Social Life of Microblogged Information. In *Proceedings of the 2010 ACM Conference on Computer Supported Cooperative Work* (CSCW '10). ACM, New York, NY, USA, 241–250. DOI: http://dx.doi.org/10.1145/1718918.1718965
43. Kate Starbird, Emma Spiro, Isabelle Edwards, Kaitlyn Zhou, Jim Maddock, and Sindhuja Narasimhan. 2016. Could This Be True? I Think So! Expressed Uncertainty in Online Rumoring. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (CHI '16). ACM Press, New York, New York, USA, 360–371. DOI: http://dx.doi.org/10.1145/2858036.2858551
44. Michael A Stefanone, Gregory D Saxton, Michael J Egnoto, Wayne X Wei, and Yun Fu. 2015. Image attributes and diffusion via Twitter: the case of #guncontrol. In *Proceedings of the 33rd Annual Hawaii International Conference on System Sciences* (HICSS '15). IEEE, 1788–1797.
45. Olivier Toubia and Andrew T Stephen. 2011. Intrinsic versus Image-Related Motivations in Social Media: Why Do People Contribute Content to Twitter? SSRN Electronic Journal (2011), 1–41. DOI: http://dx.doi.org/10.2139/ssrn.1949833
46. Sarah Vieweg, Amanda L. Hughes, Kate Starbird, and Leysia Palen. 2010. Microblogging During Two Natural Hazards Events: What Twitter May Contribute to Situational Awareness. In *Proceedings of the 28th International Conference on Human factors in Computing Systems* (CHI '10). ACM Press, New York, New York, USA, 1079. DOI: http://dx.doi.org/10.1145/1753326.1753486
47. Farida Vis, Simon Faulkner, Katy Parry, Y Manyukhina, and Lisa Evans. 2013. Twitpic-ing the riots: analysing images shared on Twitter during the 2011 UK Riots. (2013).
48. Joanne I. White, Leysia Palen, and Kenneth M. Anderson. 2014. Digital Mobilization in Disaster Response: The Work & Self-Organization of On-Line Pet Advocates in Response to Hurricane Sandy. *Proceedings of the 17th ACM Conference On Computer Supported Cooperative Work & Social Computing* (CSCW '14), ACM Press, 866–876. http://doi.org/10.1145/2531602.2531633
49. Keiji Yanai. 2012. World Seer : A Realtime Geo-Tweet Photo Mapping System. In *Proceedings of the 2nd ACM International Conference on Multimedia Retrieval* (ICMR '12). ACM Press, New York, New York, USA, 1. DOI: http://dx.doi.org/10.1145/2324796.2324870

APPENDIX

Keywords and hashtags used for Twitter collection (terms marked with * were eventually disabled):

#everest2015, #everestavalanche, #missinginnepal, #mteverest, #nepalearthquake, #nepalquakerelief, #operationmaitri,]याaqबो\, aftershock, annapurna, avalanche, baglung, bagmati, barpak, baudhanath, bhaktapur, bhimsen, biratnagar, boudha, boudhanath, brick*, chabahil, charikot, chilankha, collapse*, concrete*, damage*, dhading, dharahara, dhulikhel, dhunche, dingboche, dolakha, durbur square, ekantakuna, fail*, fire*, gandaki, ghodatabela, ghoratabela, gokyo, gorak shep, gorka, gorkha*, gorkha earthquake*, hanuman dhoka, hetauda, kaski, kathmandu, katmandu, kavre, khotang, khumjung, kirtipur, kyanjin gompa, lalitpur, lamjung, landslide, langtang, laprak, liquefaction, lobuche, lukla, makawanpur , makwanpur, manaslu, mandir, masonry*, nagarkot, namche, napal, nepal, nepalquake, nuwakot, okhaldhunga, pangboche, pashupatinath, patan, patana, phakding, pheriche, phortse, pipeline*, pokara, pokhara, pumori, ramechhap, rasuwa, sankhu, shantinagar, sindhuli, sindhupalchok, sindhupalchowk, slope*, solukhumbu, stupa, sundhara, sunsari, swayambunath, syabru, tengpoche, thamel, thangpalkot, tudikhel, अन्नपूर्ण, आगो, एकाuतक`ना, ओखलढुङ्गा, काठमाडौं, काभ्रे, कास्की, कीर्तिपुर, क्षति, खानेपानी, खुम्जुङ, खोटाङ, गण्डकी, गो:यो, गोरखा, गोर्खा, चाबहिल, जमीनको घम्काई, जोखिमहरु, झटकों, ट`aeडaल, दोलखा, धादिङ, धुलिखेल, नगरकोट, ना5\, नुवाकोट, नेपाल, पश#पeतनाथ, पाइपलाइन, पाटन, पाटन कृष्ण मन्दिर, पुमोरी, बागमती, बागलुङ्ग, बौद्धनाथ, भक्तपुर, भवन, भूकम्प, मकवानपुर, मनास्लु, माैत, रसुवा, रामेछाप, लमजुङ, ललितपुर, लोबुचे, विनाश, विराटनगर, संकट, सगरमाथा, सजा मिली, सिन्धुपाल्चोक, सिन्धुली, सुनसरीका, सुरक्षित, स्तूप, हनुमानढोका