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Understanding Social Media Beyond Text: A Reliable Practice on Twitter

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Abstract

Social media has been broadly applied in many applications in sales, marketing, event detection, etc. With high-volume and real-time data, social media has also been used for disaster responses. However, distinguishing between rumors and reliable information can be challenging, since social media, a user-generated content system, has a great number of users who update massive information every second. Furthermore, the rich information is not only included in the short text content but also embedded in the images, videos. In this paper, to address the emerging challenge of disaster response, we introduce a reliable framework for disaster information understanding and response with a practice on Twitter. The framework integrates both textual and imagery content from tweets in hope to fully utilize the information. The text classifier is built to remove noises, which can achieve 0.92 F1-score in classifying individual tweet. The image classifier is constructed by fine-tuning pre-trained VGG-F network, which can achieve 90% accuracy. The image classifier serves as a verifier in the pipeline to reject or confirm the detected events. The evaluation indicates that the verifier can significantly reduce false positive events. We also explore Twitter-based drought management system and infrastructure monitoring system to further study the impacts of imagery content on event detection systems and we are able to pinpoint additional benefits which can be gained from social media imagery content.

Keywords: social media; multimedia information; event detection

Introduction

The number of users on social media are huge. According to Our World in Data, there are 7.7 billion people in the world, with at least 3.5 billion of us online, which means one-in-three people in the world use social media [1]. Domo's Data Never Sleeps 5.0 report shows every minute of the day in 2017, there are 456,000 tweets sent on Twitter, there are 46,740 photos posted on Instagram, and there are 527,760 photos shared on Snapchat [2]. With such large volume of real-time data, social media has become an important data source in both industry and academia. It is extensively used in a wide range of topics, including monitoring outdoor air pollution in London [3], modeling rumor spreading [4, 5], preventing sensitive information attacks, achieving disease surveillance [6], detecting natural disasters [7], etc.

With high-volume and real-time data, social media can at times outperform news sources on timeliness when reporting some types of events [8, 9, 10, 11]. For instance, it is quite a hot topic that the Amazon rain forest had alarming clusters of burning wildfires in summer 2019. There was a popular comment about the delayed media coverage, which stated that "When the Church of Notre Dame was burning, media coverage was all over the place in a few hours. The rain forest of Amazon in Brazil is burning for 3 weeks but no media coverage." Power from Media Matters presented the bar chart in Fig. 1 to show the number of cable news segments mentioning the Amazon fires [12]. The first report on cable news was on August 21, 2019. However, the earliest tweet I can find about this wildfire is from August 6, 2019, as shown in Fig. 2.

Meanwhile, using social media data in event detection system raises some challenges due to high volume, noises, and lack of geo-tagged information. When designing a social media-based application for landslide detection, we might face challenges as follows. As defined in Merriam Webster dictionary, "landslide" refers to "rapid downward movement of a mass of rock, earth, or artificial fill on a slop", or "a great majority of votes for one side". When collecting tweets with the keyword, "landslides", we get tweets not only about natural disasters but also about elections, as shown in Fig. 3. Most social media limits the number of words in each post. For example, Twitter only allows 280 characters. Kokalitcheva shared that only about 1% tweets hit the 280-character limit, and 12% are longer than 140 characters [13], which means textual content of each tweet can only carry limited information.

A number of previous studies attempt to filter out noises and to understand the large data set extracted from social media. Harris et al. use geo-location information to remove irrelevant tweets [14]. Musaev et al. design text classification to filter out noises and compute relevance ranking of users to achieve better accuracy on landslide detection [15, 7]. McGough et al. include news sources, in addition to social media, to improve the accuracy on Zika incidence forecasting [16]. Researchers also explore topic analysis on social media data in hope to extract meaningful topics from massive information. Kamath et al. and Argyrou et al. propose approaches to use hashtags as a major source to identify topics [17, 18] and Cataldi et al. and Han et al. use searching queries for topic detection [19, 20].

Most of the previous studies focus on textual content of social media, and, to the best of our knowledge, there is so far no social media-based event detection application incorporating imagery content. More than likely, as shown in Fig. 3, imagery and textual content of one tweet are relevant, and images can carry high-quality and valuable information. With the rapid development of the internet speed and the promising future of 5G wireless networks, images and videos are becoming significant parts of social media. Image analysis are maturing as well. Machine learning and neural networks are available to automatically annotate images with keywords and to segment certain objects in the images. It's time to fuse textual and visual aspects of data points, and to further improve the performance of the existing social media based applications.

In this paper, we investigate what benefits images can bring to social media-based event detection systems. We use the landslide detection system as the demonstration. Imagery content is integrated into the existing system to confirm or reject the events which have been detected from textual content. We implement a pre-trained convolutional neural network to extract features from images and apply the clustering algorithm to identify potential groups. We fine-tune a pre-trained CNN to classify images for the purpose of identifying landslides. Finally, we compare the detected events from the system with and without imagery content. It shows that image analysis can help the system successfully confirm 12.46% of the detected events and reject 6.31% of the incorrectly detected events. In addition, we study tweets about infrastructure breakdowns and California drought to outlook other contributions which imagery content can provide in a social media-based information system.

The rest of the paper is organized as follows. Section 2 includes related works. Section 3 outlines the system overview. Section 4 focuses on the image analysis, including image clustering and image classification. Section 5 shows the evaluation of the multimedia information system. Section 6 discusses other potential benefits which can be gained from imagery content. Section 7 concludes the paper.

Related Work

A considerable amount of data on social media attracts researchers and companies from different fields. U.S. companies use social media, such as Twitter, to observe market trends and produce business values [21]. Twitter is used to track the spread of diseases and to monitor social commentary during the influenza H1N1 pandemic [22]. Social Media has emerged as a helpful information source in disaster management. Social media technologies were deployed as the main knowledge sharing mechanisms among US government agencies during 2010 Haitian earthquakes [23, 24]. The previous studies design Twitter-based systems to identify natural disasters and to improve situation awareness in critical times [25, 26, 27, 28, 8]. Topic modeling, a text-mining tool, is used to discover the abstract topics from a collection of data [19]. Peak detection algorithms are applied to collection of hourly tweet volumes to identify abnormal surges of communication [29]. Sentiment analysis on text from social media has become an important area of work to understand feelings and emotions of certain groups. PageRank is widely used on user networks to identify influencers in order to better control epidemic outbreaks, accelerate information propagation, conduct successful e-commerce advertisements. Most of the previous works focus on textual content, tweet volumes, and user networks. Almost no systems have explored imagery content from social media as an information source for event detection systems.

Shifting from statistical methods to deep learning neural network methods, the field of computer vision has achieved state-of-art results on several interesting and practical problems. Deep convolutional neural networks can produce promising image classification results. Image classification with localization can not only assign a class label to an image but also show the location of the object in the image by a bounding box. Object segmentation splits an image into meaningful segments and object detection classify a segment of an image. Technologies are also available to reconstructure an image by filling in missing or corrupt parts.

Understanding images and extracting information from those can be easily achieved with all the advanced technologies available in the field of computer vision. In our previous works, we have proposed to include imagery content as an information source in landslide detection system to further improve the accuracy and the coverage [30]. In this paper, we extend the experiments significantly by collecting more than 100,000 tweets about California drought and infrastructure breakdowns.

We study texts and images with clustering and classification techniques. With the extended experiments, we are able to pinpoint several additional benefits which can be gained from imagery content. The image-text mapping from social media, such as Twitter, offer us a valuable image set with text labels. Clustering images can identify major events and group together information about the same events. Furthermore, the similarity of images shared among users present a new type of user relationship.

System Overview

Fig. 4 presents the pipeline of Twitter-based landslide detection system, extended from the system proposed by Musaev. et al. [15]. Downloader: search terms, such as “Landslide”, “mudslides”, etc. are used to collect data from Twitter. Cleaner: Stop words, including “election”, “won”, etc. remove noises to some extent. Geo-tagger: Name Entity Recognizer is used to extract geo-location entities (geo-terms), and then Google Maps APIs converts geo-terms into geographic coordinates (geo-code) [31]. Text Classifier: This is another layer of filtering to further remove noises. Text is converted into vectors by Word2Vec with a pre-trained model from Google and then Support Vector Machine is used for classification [32, 33]. Detector: Geo-tagged tweets are grouped into cells by month and geo-codes. A score is computed for each cell to evaluate how likely there is a landslide happened in this cell during this month. Image Classifier Verifier: We fine-tune a pre-trained deep network, VGG-F, to classify images from tweets. The image classification results are used to reject or confirm the events from Detector.

Image Analysis

438,000 tweets are collected from 2018 with keywords “landslides”, and among these, more than 56,000 tweets contain at least one image. Tweets from January are manually labeled as relevant or irrelevant to natural disasters. We study 2,000 images from the labeled tweets to understand the imagery content and how textual and imagery content are related.

Image Labeling

We use image labeling service from Google Vision AI to capture the imagery content as a whole. Most common labels of relevant tweets are geological, road, mountain, text, and terrain and three major categories are maps, terrain, and text, as shown in Fig. 5. Most common labels of irrelevant tweets are text, font, photograph, and hair and three major categories are portrait, text, and poster, as shown in Fig. 6. Most of images from irrelevant tweets are portraits, as the word “landslides” is also used to describe elections. Additionally, there is a movie, named “landslide”, released in February 2018, leading to some movie posters in irrelevant tweets.

Image Clustering

We use Keras’ pre-trained model, VGG16, for feature extraction purpose. VGG16 is a deep convolutional network developed and trained by Oxford’s Visual Geometry Group (VGG), which achieved good performance on the ImageNet Challenge 2014 submission [34]. The input layer takes an image of the size of 224 * 224 * 3, and the output layer is a soft-max prediction on 1000 classes. The feature extraction part of the model is from the input layer to the last max pooling layer, which is the size of 25,088 (7 * 7 * 512). We apply K-means clustering method with 25,088 features to explore potential groupings. Fig. 7 presents two dominant clusters from the clustering results. A majority of the left cluster are terrain images, which mainly come from the tweets relevant to natural disasters; the right cluster includes portraits, which are from the tweets relevant to elections, and irrelevant to natural disasters. The clustering results verify our previous observations that images with terrain are typically from the tweets relevant to natural disasters, and those with portraits are more than likely from the tweets irrelevant to natural disasters.

Image Classification

To help the landslide information system confirm or reject the detected events, we would like to build an image classification model which can differentiate between terrains and portraits. A pre-trained VGG-F network is fine-tuned to achieve the task.

Donahue et al. demonstrate that features extracted from a deep convolutional network, which is trained on a large and fixed set of object recognition tasks, can be reused for novel generic tasks [35]. It might be expected that the representations of a deep network are over-fitted for one particular task, as the network is discriminatively trained to perform well at one specific task. However, surprisingly, pre-trained networks often achieve better performance than that of hand-crafted features, especially when there are limited training images.

Chatfield et al. propose VGG-F network, a simpler version of the network developed by Krizhevsky et al. It consists 8 learnable layers, 5 of which are convolutional, and the last 3 are fully connected [36]. We take the existing VGG-F network, replace the final layer with random weights, and train the network again with images labeled as terrain or portrait. We are able to achieve 87% accuracy with five training epochs.

Evaluation

438,000 tweets are collected from 2018. 40% of those are removed by stop words and about 260,000 tweets remain. There are about 114,000 tweets containing geo-terms. Since useful and valuable events should have spatiotemporal features, we only analyze those with geo-terms. Among these, 17,651 tweets, about 15%, have at least one image.

We use the annotated landslides data set published by GRAIT-DM [37] to evaluate the text classifier. The data set contains about 4,000 tweets from 2014. The first three months' tweets are used as testing set and the rest as training set. SVM is used to classify tweets as relevant or irrelevant to landslides. The average F1-score is about 0.92, and the detailed evaluation is shown in Table 1. The classifier produces good recall with the average as 0.96. Recall is the fraction of the relevant text that are successfully classified as relevant. However, precision is not promising, with the average as 0.89. Precision is the fraction of the classified as relevant text that are relevant. The result indicates with image classification verifier, the pipeline can manage to collect most of the true events but might report a number of false events. To advance the existing pipeline, imagery content is used as a verification in hope to reduce false positives.

2000 images from January 2018 are labeled as portrait, terrain, or others. The images are resized to 224 * 224; images are normalized by subtracting the mean. With five training epochs, the model can achieve about 86% accuracy. The detailed performance of the image classifier is shown in Fig. 8. The left pane shows the training loss and validation loss by training epochs. Whenever the network makes mistakes, a loss is calculated, and backpropagation algorithm updates the weights of the network in the direction that will decrease the loss. The middle one presents the training and validation accuracy with top 1 error (how often the highest scoring label is wrong). The right one shows top 5 error.

We compare the events detected by the pipeline with and without image classifier. 42,000 tweets are classified as relevant to landslide disasters. The surface of the earth is considered as a grid consisting of cells. Each cell is roughly equal to 3 miles by 3 miles. The tweets are grouped into cells based on their geo-codes and month. Detector reports an event in cell (0,0) from January 2018, if there are more than 10 tweets from January 2018 grouped in cell (0,0).

Table 2 presents the number of events detected by the system. About 28% of events have at least one images. Image classifier is applied on these images. Verifier confirms the detected events if 60% images from the event are classified as terrain and it rejects the detected events if 60% images from the event are classified as portrait. We manually verify the events rejected by image classification results. The evaluation confirms Verifier can help the system reduce false positive events and improve the accuracy of the detected events.

Discussion

To further study potential benefits from imagery content, we incorporate images into the existing social media-based event detection systems and explore what can be gained from the new type of information. We focus on three Twitter-based systems in this section. (1) Musaev et al. propose a pilot study about social response to California drought through Twitter. They apply PageRank on retweeting activities to identify key drivers in the community and create word clouds with textual content to understand the current drought response plans [38]. (2) Musaev et al. generate a map of detected road problems based on Twitter data. The sentiment score is computed with textual content. They want to provide novel perspectives on the state of road infrastructure to help guide decisions related to road infrastructure funding [39]. (3) Tien et al. recommend using social sensor to detect failure events or damages in main infrastructure systems, including bridges, highways, gas lines, and power infrastructures, in hope to compensate the lack of continuous physical monitoring sensors. They develop three-step filtering approach on text to filter out noises in social sensors [40].

We collect about 100,000 tweets about California drought and infrastructure breakdowns between January 2018 and December 2019 with keywords listed in Fig.9. There are about 23% tweets containing at least one image. We use VGG16 to extract features from the images. Principal Component analysis is used to extract the first three principal components. Then, K-means clustering is applied to help us understand imagery content as a whole.

The clustering results of road data with five cluster centers are displayed in Fig. 10 and sample images from each cluster can be found in Fig. 11. Cluster 0 are dominated by asphalt and dirt roads. Most images in cluster 4 and cluster 1 contain road surfaces, but there are also major objects in the images, such as a person, a car, or a tire. Images with dramatic colors are in cluster 3 and maps and tables are in cluster 2. The clustering results provide us an overall understanding of the tweets' content and help us identify hidden groups. By exploring collected images, we uncover several additional benefits of integrating imagery content into the existing event detection pipelines.

Ease training data preparation for text classification. Researchers are interested in achieving event detection with data from social media, since social media is producing a large amount of information in real time. However, unlike designated physical sensors or authoritative information sources, there are abundant noises in data collected from social media. Text classification is one of the approaches to filter out noises. As a supervised machine learning algorithm, text classification requires a large amount training data and preparing training data is often really expensive. Image clustering results can potentially help ease the preparation of training data for text classification. Furthermore, text and image from one tweet are presumably related, which offers us a valuable text-image mapping. The mapping enables a knowledge transfer between the two type of information. Addition to social media related studies, the text-image mapping can benefit a broader range of researches which demand either imagery or textual data sets.

To gain knowledge about textual content of the data set, we apply clustering on the texts. Term frequency-inverse document frequency is used to obtain term weight. PCA is used to identify the first three principal components. K-means clustering is applied. The result can be found in Fig. 12 and sample images from each cluster can be found in Fig. 13. 90% of the images from cluster 1 are "image not found" or "file not found". We explore the text further in cluster 1 and find an interesting word with high frequency, "FixMyStreet". By reading the original tweets, we find tweets in cluster 1 are sharing information from FixMyStreet, a service to map and report street problems to the councils responsible for fixing them in the UK [41]. Majority of the images in cluster 2 are about travel and almost all the tweets in cluster 2 contain the quote "stop worrying about the potholes in the road and enjoy the journey". Clustering results of both imagery and textual content present us thorough insights about the tweets we collect on road damages. The sharpened understanding of collected data will eventually lead to an improved event detection system.

Pinpoint the major events and bring together information about the same events. We apply image clustering on tweets about highways. By analyzing the clustering results, we are able to identify two major highway breakdowns in 2018. As shown in Fig. 14, cluster 4 shows that a pedestrian bridge collapsed over Miami highway in Florida, USA, in March 2018 and cluster 5 displays the collapse of the Morandi bridge in Genoa, Italy, in August 2018. The clustering algorithm groups together images about the same events. Combining the images from different angles equips us with a more in-depth awareness of the situation. It will be exciting to the audience if the social media-based system includes a group of images on the detected events to demonstrate a comprehensive perspective of the major events.

Present a new type of user relationship. As shown in Fig. 14, the clustering result of highway data presents us cluster 5, a cluster with the duplicate images, which are from a news source, Edmonton Journal [42]. The news is about a company's collapse which leaves contracts for thousands of kilometers of Alberta highways in question. These tweets share the same news, but they don't have any interactions on Twitter. There are previous works dedicating to studying user networks on social media to understand how information flow and who contributes to information diffusion. The previous works focus on the network, consisting the five major types of user interactions, being tagged on post, commenting post, sharing post, liking post, and following others. Sharing same or similar images can be a new type of relationship on social media to assist the study of network analysis and information flow.

Present time series information about an event. We also apply image clustering on California drought data. An interesting cluster contains about 600 heatmaps, showing California drought conditions, as shown in Fig. 15. The sequence of images demonstrates the change of drought conditions in California in 2019. Social media can serve as a valuable information source to provide a series of images about one event or one geographic location over a long period of time. The time series data can assist the studies of changes and trends.

Conclusion

Social media data has been widely used as an information source in event detection systems. We propose a landslide information framework which integrates both textual and imagery content from tweets in hope to fully utilize the information. The evaluation indicates that image classification results can successfully reduce false detected events. By exploring images from tweets in other areas, we also identify additional benefits which can be gained from analyzing images.

The fast development of computing capabilities and the promising future of 5G wireless reveal that images and videos are becoming leading formats to carry information. With all the advanced technologies available to analyze images, it's time to fuse imagery content into event detection systems to further expand input data, so that output results can be further improved. For systems dedicating to raise situation awareness during disasters, images can help first responders better understand the conditions of the affected areas. For those interested in studying trends over time, Twitter is a good resource to collect a series of images from one geographic locations or images about one object over a long period of time. The image-text mapping from Twitter is valuable for researches in diverse fields, especially those interested in having labeled images for training data set.

In the future works, we would like to package the image analysis stage of the proposed pipeline into a self-contained block, so that the block can be easily added into other existing event detection systems which consume social media data. The block provides a fast approach for the existing systems to benefit from imagery content.

Authors' contributions
QH and MH participated in the design of the study and performed the text and image analysis. QH, MH, and FQ co-authored the manuscript. All authors read and approved the final manuscript.

Availability of data
The data sets analyzed during the current study are available at https://github.com/qixuanHou/SocialMediaBeyondText.

Competing interests
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Table 1 Evaluation of text classifier with the annotated tweets from 2014.

2014	January	February	March
Precision	0.88	0.90	0.90
Recall	0.98	0.93	0.97
F1 score	0.93	092	0.93

Table 2 The events confirmed or rejected by image classifier.

2018	1	2	3	4	5	6
# events detected without images	121	43	102	96	87	89
% events detected with images	26.45%	30.23%	27.45%	25.00%	24.14%	25.84%
% events rejected by images	6.61%	6.98%	6.86%	5.21%	3.45%	5.62%
% events confirmed by images	12.40%	16.28%	13.73%	10.42%	14.94%	11.24%

2018	7	8	9	10	11	12
# events detected without images	93	68	61	78	74	59
% events detected with images	26.88%	26.47%	39.34%	29.49%	25.6%	35.59%
% events rejected by images	8.60%	8.82%	6.56%	3.85%	8.11%	5.08%
% events confirmed by images	7.53%	8.82%	19.67%	11.54%	9.46%	13.56%