EMAssistant: A Learning Analytics System for Social and Web Data Filtering to Assist Trainees and Volunteers of Emergency Services

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ABSTRACT

An increasing number of Machine Learning based systems are being designed to filter and visualize the relevant information from social media and web streams for disaster management. Given the dynamic disaster events, the notion of *relevant information* evolves, and thus, the active learning techniques are often considered to keep updating the predictive models for the relevant information filtering. However, the active relevant feedback provided by the human annotators to update the models are not validated. As a result, they can introduce unconscious biases in the learning process of humans and can result in an inaccurate or inefficient predictive system. Therefore, this paper describes the design and implementation of an open-source technology-based learning analytics system '*EMAssistant*' for the emergency volunteers or practitioners - referred as the trainee, to enhance their experiential learning cycle with the cause-effect reasoning on providing relevant feedback to the machine learning model. This continuous integration between the cause (providing feedback) and the effect (observing predictions from the updated model) in a visual form will likely to improve the understanding of the trainees to provide more accurate feedback. We propose to present the system design as well as provide hands-on exercises for the conference session.

Keywords

Training System, Disaster Management, Active Learning, Humanitarian Technology, Social Media Mining

INTRODUCTION

There is a growing number of sources sharing situational updates during a disaster event via social media as well as other web platforms such as news feeds that lead to the phenomenon of *big crisis data* (Castillo, 2016). These situational updates include time-critical reports (Imran et al., 2013) as well as requests and offers to help (Purohit et al., 2013) such as through Facebook's recently launched 'Community Help' feature. Moreover, given the ubiquitous adoption of Internet-based communication by the public, the importance of mining the big crisis data streams in the expectation of extracting the time-critical, relevant situational information to assist emergency management agencies has grown tremendously in the recent years (U.S Homeland Security, 2014; Hughes and Palen, 2012; Hiltz et al., 2014; Meier, 2015). Also, as per recent surveys (Reuter and Spielhofer, 2017; Canadian Red Cross, 2018), there is a growing expectation by the public to seek a response from the emergency services through an online medium, especially social media. However, the characteristics of big crisis data like high volume, velocity, and variety issues can create a challenge of timely extracting situational information from social and web data streams.

Researchers in the crisis informatics and disaster management have investigated many approaches in the last two decades to understand, process, and manage the streaming big crisis data, in order to provide systematic access to the relevant information (*c.f.* survey Imran et al., 2015). The analytical approaches primarily include mining user-level information (e.g., onsite witnesses (Starbird et al., 2012), trustworthiness (Tapia et al., 2011)), content-level information (e.g., topical categories (Imran et al., 2013), help behavior (Purohit et al., 2014)) as well as network-level (e.g., retweetability prediction (Neppalli et al., 2016)) and context-level (e.g., location (Al-Olimat et al., 2018)) information.

There have been several efforts in the last decade to develop systems that implement the above-discussed analytical approaches for assisting emergency management organizations. Such existing analytics systems incorporate multiple data sources and often with different modalities to study a disaster event in real time as well as retrospective view (e.g., TweetTracker (Kumar et al., 2011), Twitcident (Abel et al., 2012), CrisisTracker (Rogstadius et al., 2013), Truthy (McKelvey and Menczer, 2013), AIDR (Imran et al., 2014), Twitris (Sheth et al., 2017), CitizenHelper-Adaptive (Pandey and Purohit, 2018)).

However, the majority of the existing systems rely on the prebuilt machine learning models using the datasets from the prior events alone to train and set up the analytical system for a current event. It is because there are very few training data instances available at the onset of a new disaster event to build a robust machine learning model. For overcoming that, researchers have used active learning techniques to frequently update the prebuilt model with expert feedback for addressing the performance issue of the misprediction in continuous data streams (e.g., CitizenHelper-Adaptive (Pandey and Purohit, 2018); AIDR (Imran et al. 2014)). However, due to the increasing workload of the expert emergency management professionals during time-critical crisis operation, it is challenging to learn to provide effective feedback for relevant information at the same time. Additionally, given the increasing trends of leveraging help from crowdsourcing, they want to rely on operationally non-expert volunteers to do this task of providing relevance feedback on the data stream to improve the machine learning based information filtering system. Thus, covering all the aspects of training the practitioner trainees as well as volunteers can be costly both in terms of money and time for the emergency services.

Thus, we address two key problems in our proposed system design. First, the input data stream is sometimes hard to comprehend due to the changing definition of relevance (issue of concept drift), which can be mitigated by frequently informing the trainee through the effects of providing feedback to a diverse set of message instances from the ground truth. Second, the trainee/volunteer may possess certain bias in learning the patterns of what constitutes a relevant message as reflected in the feedback provided by him/her, which can be mitigated by showing the trainee/volunteer the performance of the updated (weak) prediction model frequently.

We propose *EMAssistant — Emergency Management Assistant*, an open source technology-based learning analytics system that will assist emergency management trainees to provide accurate feedback in improving a machine learning model for information filtering tasks. The system provides a web-based learning platform for the trainee by constantly re-training the model from the feedback provided by them and then visualizing a few expert-labeled data based on the error comparison of its predicted and original labels. We are also utilizing expert-labeled data along with the trainee's feedback for robust re-training of the model. As soon as the trainee observes that the error effect has been minimized consistently, they will be ready to provide the feedback in a real-time environment and contribute to the data-driven disaster management information filtering tasks. The resulting system is cost effective since it can be adapted to any social media mining problem beyond the information filtering task for the emergency services; for example, in training the student practitioners for data analytics with the state-of-the-art techniques. The rest of the paper is organised as follows. We first discuss related work on the systems designed for disaster management. We then describe the design of our proposed system architecture, followed by the analysis of the proposed tool with an illustration of the system's functionality using a past disaster event dataset. The conclusion summarizes our plan for the demo, exercises during the conference session, as well as the directions for future upgrades for the system.

RELATED WORK ON DISASTER ANALYTICS SYSTEMS

We describe state-of-the-art tools in the crisis informatics and disaster management literature.

Recent advancement in technologies has brought more engagement during emergency and disaster management for the emergency practitioners, the crowdsourcing volunteers, and the affected communities. This has led to the flood of shared information on social and web platforms that can be utilized to do what was earlier not possible in disaster management. However, since most of the incoming data is unstructured, many research works have been done to extract semantically structured information (Garcia-Santa et al, 2015).

I-REACT (I-REACT Project, 2018) is an example of one such platform that uses both mobile and web platforms to offer better anticipation of extreme weather events, floods, and fire with historical knowledge, satellite and risk maps, crowdsourced reports, and social media information. In addition, many crowdsourcing tools are used for extracting the relevant information from unstructured data streams that include a variety of methods, such as natural language understanding, multisource data collection, filtering, tagging, mapping and navigation, volunteer management, and crowdsourcing roles tools. Prior work on web-based, as well as mobile-based platforms, can be classified into 4 categories based on tools functionality: Crisis Mapping, Crisis Navigation, Volunteer Management Tools, and Ontologies (Poblet et al., 2017).

Among the web-based platforms, Twitris (Sheth et al, 2014) and iCoast (Liu et al., 2014) are two examples used for crisis data analytics and crisis mapping. Twitris involves real-time analysis of social sensing and perception for disaster response including earthquakes, hurricanes, tornados, and floods. iCoast gives a platform to volunteers to upload an informative aerial photograph of the affected area in a disaster event for crisis mapping. For crisis navigation, OSMTracker is a mobile-based application that collects track logging and navigational information from users. Similarly, many tools are available for volunteers management like GeoTag-X (Jennett & Cox, 2014), CrowdCrafting (Sánchez de Miguel et al., 2015), Micromappers (Ofli et al., 2016), Tomnod(Lin et al,, 2014), and Verily (Meier et al., 2013). GeoTag-X, for example, uses volunteers to analyse photo taken in disaster-affected areas, while Crowdcrafting is used in the analysis of data or challenging tasks with the help of volunteers. Furthermore, Micromappers uses human intelligence to get semantic information from unstructured data and Tomnod asks volunteers to identify important objects in satellite images during the crisis. In addition, Verily helps to mitigate false information spread during a disaster with the help of crowdsourcing volunteers. There are also mobile-based crowdsourcing tool like UN Assign (Bæhr, 2016), FemaApp, and FirstToSee that are used for crisis mapping by allowing the user to upload geotagged pictures in the disaster-affected area. Finally, AIDR (Imran et al., 2014) - Artificial Intelligence for Disaster Response provides a platform to create ontologies. It is then used to perform automatic classification of messages that people post during disasters into given ontologies for large-scale data at high speed.

We can observe that a lot of the existing systems depend on volunteer's contributions. Yet, there are no prior systems that tackle another core functionality of crisis management platform i.e. learning analytics system to these volunteers. Most of the system assumes that the volunteers either have significant knowledge or are trained before for better interacting with the system. However, it is not always the case and training volunteers on a large scale can be very expensive. That's why our proposed method will not only help train volunteers in scale but also in a cost-effective way. The little involvement of the humans in the proposed system makes it scalable. Figure 1 shows the architecture of our system and Figure 2 shows an illustration of our main system of providing the feedback and observing the effects respectively.

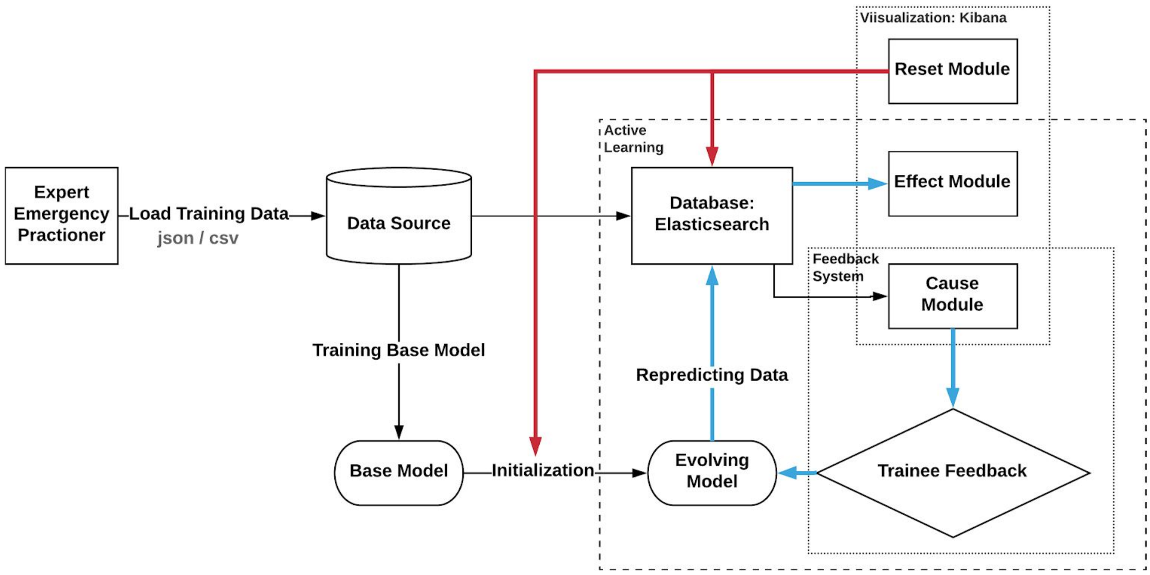

Figure 1. System architecture of EMAssistant

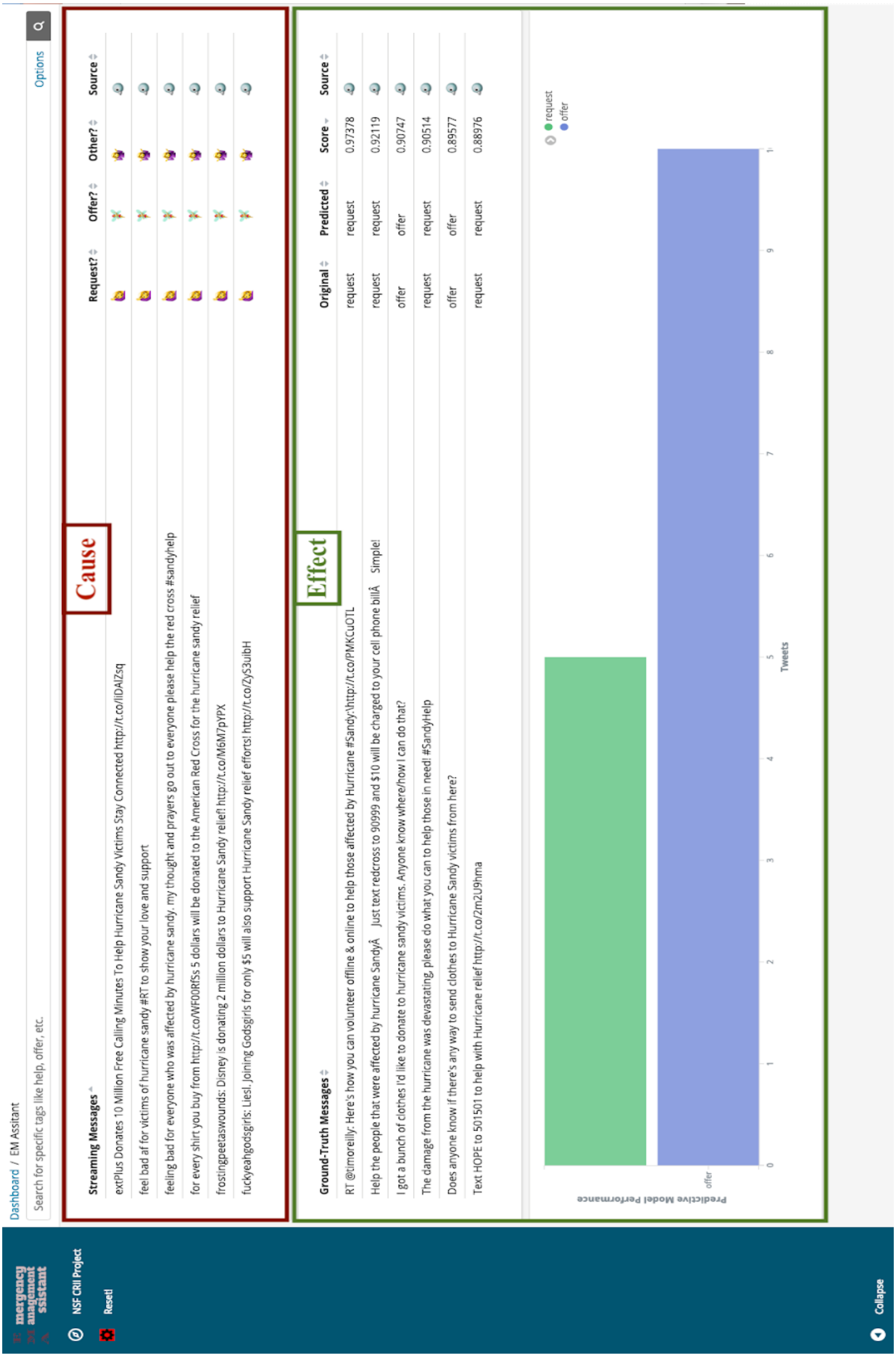

Figure 2. Illustration of analysis using EMAssistant system feedback

EMERGENCY MANAGEMENT ASSISTANT SYSTEM (*EMAssistant*)

This section describes the architectural pipeline for various features of the proposed *Emergency Management Assistance System* which provides a training mechanism to emergency practitioners using active machine learning capabilities. The system architecture of EMAssitant is shown in Figure 1. It consists of 4 main modules: *Data Loading, Training Model, Active Learning, and Visualization*. The blue arrow indicates the feedback-based model re-training cycle and the red arrow shows the effects of the reset functionality on the database and base model initialization.

A. Data Loading

We used the expert labeled data collected from Emergency Practitioners (EM). These labels in the data act as ground truth for training the model. The data is then loaded in the ElasticSearch Database. While loading the data, few of the data points were marked to observe and visualize the effects in the *Ground Truth Visualization* and *Predictive Model Performance Visualization* components of Kibana.

Both Elasticsearch and Kibana are open source projects where Elasticsearch is a searching and analytics engine that provides distributed, RESTful, JSON based search engine that makes it highly scalable and flexible for a large amount of data. On the other hand, Kibana lets us visualize data in the form of various dashboards which includes graphs and table. We have integrated stacked bar chart under *Predictive Model Performance Visualization* which assists the trainee to efficiently visualize the per class effects based on the feedback provided. Kibana and Elasticsearch work exceptionally well together and provides rapid deployment for a variety of custom visualizations as needed for various EM exercises. Kibana also provides scripted fields that can help to create custom URL links for each message object. We have used this feature to generate URLs to call an API and it acts like a button in the enhanced-table visualization that is used by both *Streaming Message Visualization* and *Ground Truth Visualization*. Trainee uses these buttons to give feedback as a result of which our API is called, which re-trains the model and update the *Ground Truth Visualization*. One more reason to choose Kibana was that the dashboards created under Kibana are automatically refreshed after every 5 seconds, thus provides a real-time visualization of the effects as per the feedback provided by the trainee.

B. Training Model

Based on the expert labels provided by the Emergency Practitioners we build a model to classify high-level content and behavior information, such as intents like request or offering help during crisis management. We first create a base model that is trained on the initial expert labels. We have ignored the messages marked for *Ground Truth Visualization for training*. For the features generation, we have used the traditional *Bag of Words* (BoW) features (Witten et al., 2016) and for training, we have used a linear logistic regression model. Now once the adequate feedback is provided, we create an evolving model from the initial training data with the updated labels (from feedback) using the same parameters of linear logistic regression classifier. This evolving model is then used to predict the intent label of the data points that were marked for *Ground Truth Visualization*.

C. Active Learning

We have designed a feedback-based active learning approach for the trainee to continuously learn based on visualizing the cause and effect due to the feedback provided on the training model. For instance, considering the data in an emergency situation, whether the incoming messages are classified as a request, offer or other intent. For making the model train and evolve actively, the trainee will first provide the feedback in the *Streaming Message Visualization* and then observe the effects under *Ground Truth Visualization*. More specifically, we have used two parameters in our ground truth messages visualization: original and predicted. Based on the feedback provided by the trainee, the system will update the training data with the new labels and retrain the model. We use this evolving model to re-predict the data existing in the *Ground Truth Visualization* table and store the updated labels in *Predicted* column whereas the *Original* column remains the same. In this way, the trainee can see the effects of the updated model through comparison between predicted labels and original ground truth labels under *Ground Truth Visualization* table. Every time based on the volunteer action, the model will be retrained and changes will get reflected in the dashboard, which acts as a continuous learning process until the trainee observes no change in the original and predicted values and that's how bias possessed by the trainee will be removed and the trainee is ready to provide accurate feedback in real time operational environment.

D. Visualization

We have used the Kibana visualization framework for interacting with the analyzed data. Figure 2 represents our system's visualization. Our visualization has been divided into four main sub-components.

1. Streaming Message Visualization
2. Ground Truth Visualization
3. Predictive Model Performance Visualization
4. Reset Functionality

1. *Streaming Message Visualization*: This visualization will provide an interface for the volunteer to provide feedback on the messages and annotate it as a relevant label category. It contains 5 columns. The first column represents the text that shows the message text. Second, third, and fourth columns show a link to provide the feedback of request, offer, or other intent categories respectively. Finally, the fifth column contains the link to the original Twitter source of the message.

2. *Ground Truth Visualization*: This visualization will act as a learning interface for the trainee where one will see the impact of the feedback provided under the *Streaming Message Visualization*. Each message under this visualization will show the original and predicted values where original stores the ground truth and predicted stores the labels predicted by the re-trained model. Apart from these, the score field will store the confidence score calculated by the prediction probability method of the model for each message in which the higher average scores of correct predictions represents better feedback provided. The volunteer will keep on providing feedback until the original and predicted labels become the same and the overall average confidence score increases or reach to its *best* possible value.

3. *Predictive Model Performance Visualization*: This is represented through a stacked bar chart visualization that displays out of each ground truth labels, how many were correctly predicted in the intent label.

4. *Reset Functionality*: Volunteer can go back to the initial stage of learning using the reset button. This will take the model back to its initial stage and reset the intent label back to the ground truth label in the Elasticsearch as a result, the evolving model will be replaced by the base model.

ILLUSTRATION OF LEARNING ANALYTICS USING *EMAssistant*

For the analysis, we have used data collected from Twitter for Hurricane Sandy, which was the most destructive hurricane of 2012 in Atlantic. Our aim is to teach volunteers to provide feedback if the messages can be classified as the intent of requesting help, offering help, or none (Pandey and Purohit, 2018). We have labels validated from emergency experts and crowdsourcing workers or volunteers that will help build the base model to compare the effects. The reason why we have taken these intent labels is due to the fact that they can induce concept drift. For example, tweet like *"I am 9 ft above water levels, why am I told to evacuate now? Please advise"* is of a request for rescue intent category. On the other hand, tweet like *"Wow didn't realize how bad this hurricane was. #SandyHelp donate 10 dollars to help. Text REDCROSS to 90999"* is of a request for donation intent category. We can observe that even both the message should be under the *request* intent category, their semantics are different. These concept drifts can confuse the trainee and make it hard for them to comprehend and classify both the type correctly as "request" intent in the first go. Thus, to overcome this challenge, our learning analytics system helps the trainee to understand this change in concepts by providing a diverse message to get feedback and observe the effects continuously until they learn. As a result, we propose a case study where we visualize the effects of the feedback provided on the machine learning model. For illustration, we will visualize the *Ground Truth Visualization* to observe the comparison between original and predicted intents and the scores by which the intents have been predicted. We have provided 3 snapshots of the *Ground Truth Visualization*, which represents the effect due to "bad", "good", and "best" feedback respectively. The *Ground Truth Visualization* constitutes of 5 fields: *Tweet Messages*: displays the incoming messages, *Original*: displays the ground truth label associated with message, *Predicted*: displays the predicted intent label based on the updated model from feedback, *Score*: displays the confidence score of the predicted intent label, and *Source*: which redirects to Twitter for that specific message. Figure 3 represents the *Ground Truth Visualization* due to *"bad"* feedback. As we can see, apart from the 4 tweet messages of *offer* intent category, every other message has been incorrectly classified to *other* intent category. Even the ones that are classified correctly, have very low confidence score. In Figure 4, which represents the *Ground Truth Visualization* due to "good" feedback, we can see that every message has been correctly classified. The overall confidence score is also much higher as compared to the *"bad"* feedback. Finally, in Figure 5, which represents the *Ground Truth Visualization* due to the "best" feedback, we can see every message has been correctly classified with high average confidence score compared to the one due to *"good"* feedback (Figure 4). The trainee will continue to be in a situation corresponding to any of the 3 effects until they reach a point when they will finally observe the effects due to *"best"* feedback consistently and thus, will get trained.

Tweet	Original	Predicted	Score	Source
Consider donating to the Red Cross or another org to help the people affected by Hurricane Sandy. Over 60 dead. http://t.co/QWwpQzyz	request	other	0.76122	
Help the people that were affected by hurricane SandyÂ Just text redcross to 90999 and $10 will be charged to your cell phone billÂ Simple!	request	other	0.74769	
Text HOPE to 501501 to help with Hurricane relief http://t.co/2m2U9hma	request	other	0.68979	
Does anyone know if there's any way to send clothes to Hurricane Sandy victims from here?	offer	other	0.67148	
The damage from the hurricane was devastating, please do what you can to help those in need! #SandyHelp	request	other	0.67070	
does anyone know if there a local drop-off center in frederick to donate clothes to victims of hurricane sandy??	offer	other	0.64715	
Does anyone know anyways to volunteer / help hurricane sandy victims. #replytweet	offer	other	0.63518	
RT @SocialKristen: Does anyone know where in westchester I can bring clothes/donations for hurricane victims? #HurricaneSandy #helpsandy ...	offer	other	0.62326	
RT @timoreilly: Here's how you can volunteer offline & online to help those affected by Hurricane #Sandy:\http://t.co/PMKCuOTL	request	other	0.59943	
I want to donate clothes for Hurricane Sandy Relief. I just need time find out where.	offer	offer	0.56512	
I want to donate blood to the hurricane victims but it hasn't been long enough since my last donation ?? #thestruggle	offer	offer	0.55462	
@JENNIWOWW Hey girl! I have TONS of cute shoes & purses I want to donate to hurricane victims - do you know where I can send them? #Sandy	offer	offer	0.54578	
I have clothes that I'd like to donate to Hurricane Sandy victims, anyone know of drop off places for me to take them to in Jersey/NY?	offer	offer	0.51486	
I want to raise money to help the victims of Hurricane Sandy	offer	other	0.49353	
I got a bunch of clothes I'd like to donate to hurricane sandy victims. Anyone know where/how I can do that?	offer	other	0.47025	

Figure 3. Case Study: Effect table due to *"bad"* feedback for Intent classification in Hurricane Sandy

Tweet	Original	Predicted	Score	Source
RT @timoreilly: Here's how you can volunteer offline & online to help those affected by Hurricane #Sandy:\http://t.co/PMKCuOTL	request	request	0.96871	
I got a bunch of clothes I'd like to donate to hurricane sandy victims. Anyone know where/how I can do that?	offer	offer	0.92516	
Help the people that were affected by hurricane SandyÂ Just text redcross to 90999 and $10 will be charged to your cell phone billÂ Simple!	request	request	0.91010	
The damage from the hurricane was devastating, please do what you can to help those in need! #SandyHelp	request	request	0.89985	
Does anyone know if there's any way to send clothes to Hurricane Sandy victims from here?	offer	offer	0.89145	
Text HOPE to 501501 to help with Hurricane relief http://t.co/2m2U9hma	request	request	0.88794	
RT @SocialKristen: Does anyone know where in westchester I can bring clothes/donations for hurricane victims? #HurricaneSandy #helpsandy ...	offer	offer	0.86222	
I want to donate blood to the hurricane victims but it hasn't been long enough since my last donation ?? #thestruggle	offer	offer	0.84954	
does anyone know if there a local drop-off center in frederick to donate clothes to victims of hurricane sandy??	offer	offer	0.84895	
Consider donating to the Red Cross or another org to help the people affected by Hurricane Sandy. Over 60 dead. http://t.co/QWwpQzyz	request	request	0.83761	
I have clothes that I'd like to donate to Hurricane Sandy victims, anyone know of drop off places for me to take them to in Jersey/NY?	offer	offer	0.82580	
@JENNIWOWW Hey girl! I have TONS of cute shoes & purses I want to donate to hurricane victims - do you know where I can send them? #Sandy	offer	offer	0.79729	
I want to donate clothes for Hurricane Sandy Relief. I just need time find out where.	offer	offer	0.76665	
Does anyone know anyways to volunteer / help hurricane sandy victims. #replytweet	offer	offer	0.75840	
I want to raise money to help the victims of Hurricane Sandy	offer	offer	0.60367	

Figure 4. Case Study: Effect table due to *"good"* feedback for Intent classification in Hurricane Sandy

Tweet	Original	Predicted	Score	Source
RT @timoreilly: Here's how you can volunteer offline & online to help those affected by Hurricane #Sandy:\http://t.co/PMKCuOTL	request	request	0.97386	
Help the people that were affected by hurricane SandyÂ Just text redcross to 90999 and $10 will be charged to your cell phone billÂ Simple!	request	request	0.92181	
The damage from the hurricane was devastating, please do what you can to help those in need! #SandyHelp	request	request	0.90814	
I got a bunch of clothes I'd like to donate to hurricane sandy victims. Anyone know where/how I can do that?	offer	offer	0.90686	
Does anyone know if there's any way to send clothes to Hurricane Sandy victims from here?	offer	offer	0.89312	
Text HOPE to 501501 to help with Hurricane relief http://t.co/2m2U9hma	request	request	0.88886	
RT @SocialKristen: Does anyone know where in westchester I can bring clothes/donations for hurricane victims? #HurricaneSandy #helpsandy ...	offer	offer	0.85414	
does anyone know if there a local drop-off center in frederick to donate clothes to victims of hurricane sandy??	offer	offer	0.85344	
Consider donating to the Red Cross or another org to help the people affected by Hurricane Sandy. Over 60 dead. http://t.co/QWwpQzyz	request	request	0.84581	
I want to donate blood to the hurricane victims but it hasn't been long enough since my last donation ?? #thestruggle	offer	offer	0.84296	
I have clothes that I'd like to donate to Hurricane Sandy victims, anyone know of drop off places for me to take them to in Jersey/NY?	offer	offer	0.82696	
@JENNIWOWW Hey girl! I have TONS of cute shoes & purses I want to donate to hurricane victims - do you know where I can send them? #Sandy	offer	offer	0.79860	
Does anyone know anyways to volunteer / help hurricane sandy victims. #replytweet	offer	offer	0.76849	
I want to donate clothes for Hurricane Sandy Relief. I just need time find out where.	offer	offer	0.76196	
I want to raise money to help the victims of Hurricane Sandy	offer	offer	0.61393	

Figure 5. Case Study: Effect table due to *"best"* feedback for Intent classification in Hurricane Sandy

CONCLUSION AND EXERCISE PLAN

We have introduced a learning analytics tool *EMAssistant* to assist the trainees based on cause and effect visualizations from the data labeled by the experts during the emergency situation. The system will create a base model that will be actively re-trained from the feedback provided by the trainee. This will make the trainee adaptive to handle any upcoming emergency situation. The gradual learning process will make the trainee unbiased, which further makes them confident to provide feedback in real time environment. We plan to further design and evaluate learning modules guided by the human learning theories from educational psychology.

We will provide a hands-on of the *EMAssistant* tool during the conference session. Also, for the live demo and hands-on exercise session, we will provide the attendees different expert-labeled training datasets for many downstream applications of crisis management, such as topic classification (Olteanu et al., 2015), help intent classification (Purohit et al., 2013), and damage classification (Alam et al., 2018). A user survey will be conducted for the session attendees to provide input to improve the design, functionality, and the user experience of the system.

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