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Social Media Behaviour Analysis in Disaster-Response Messages of Floods and Heat Waves via Artificial Intelligence

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Abstract

This paper analyses social media data in multiple disaster-related collections of floods and heat waves in the UK. The proposed method uses machine learning classifiers based on deep bidirectional neural networks trained on benchmark datasets of disaster responses and extreme events. The resulting models are applied to perform a qualitative analysis via topic inference in text data. We further analyse a set of behavioural indicators and match them with climate variables via decoding synoptical records to analyse thermal comfort. We highlight the advantages of aligning behavioural indicators along with climate variables to provide with 7 additional valuable information to be considered especially in different phases of a disaster and applicable to extreme weather periods. The positiveness of messages is around 8% for disaster, 1% for disaster and medical response, 7% for disaster and humanitarian related messages. This shows the reliability of such data for our case studies. We show the transferability of this approach to be applied to any social media data collection.

Keywords: data collections, humanitarian information, message filtering, behaviour indicators, climate variables

1. Introduction

In the context of crisis and disaster management, advisory documents are becoming available to explore how different regions address crisis and disaster events from their governmental institutions. For instance, the Centers for Disease Control and Prevention (CDC, 2018) from the

U.S. Department of Health & Human Services provide with guidance in terms of preparedness andpromoting safe practices about how and when to inform about hurricanes, flooding and similar

disasters. Similarly, the U.K. Department for Environment Food & Rural Affairs developed a summary of recommendations in response to the multi-agency flood plan specially in terms of resilience and resource funding. In the case of heat waves, there is a visual electronic source fromthe U.S. National Weather Service (NOAA, 2020), which is provided with extensive advice in heat safety for summer 2020. More generally, a review article in global health from (Leaning & Debarati,2013) described the main natural or mankind events that caused the serious challenges for publichealth, and a guide in emergencies was published by the John Hopkins and Red Cross Red Crescent(J. Hopkins & R. Cross & R. Crescent, 2008).

Over time, social media data have been every day more considered an important source of additional knowledge to be integrated in the analysis for responding to crisis and disaster. However, the use of social media data is challenging in many different aspects, which have to do with filteringvaluable and reliable information in nearly real-time and detect hot spots where to action when anevent occurs or is about to happen. Besides, novel works in sentiment analysis and engagement prediction have shown to support the analysis by the combining social sensing with multiple machine learning approaches.

This paper presents a qualitative analysis of the application of our methodology framework, designed to combine and apply artificial intelligence (AI) modules, which provide novel insights in thecontext of disaster response. We base on a filtering approach to subsequently apply topic inferencemodels on data collections for heat waves and floods. These techniques are used both to identify relevant categories and to provide a semi-automatic approach to feedback the system with relevantmessages from key user accounts. The filtering framework approach consists of elements to extractraw messages from social media data and to detect those belonging to relevant categories through multiple deep learning classifiers. The models for these classifiers learn main disaster-related categories via fine-tuning deep bidirectional Transformer neural network models, which are shown to boost performance in benchmark datasets of disaster response and extreme events. Then, we compute hand-crafted features modelled via Latent Dirichlet Allocation (LDA) method to infer frequent disaster-related terms, and hence to statistically identify relevant topics. Lastly, we perform sentiment analysis and identification of behaviour indicators in our data collections, along with a decoding process of climate variables for the joint analysis of thermal comfort.

2. Literature Survey of Social Media Data Analysis of Disasters

This section presents a review of the state-of-the-art of social media data (SMD from now) analysisin disasters.

The U.S. Department of Homeland Security (SAVER, 2013) proposed innovative uses of social media for emergency management. Moreover, the book from (National Academies, 2007) offers a detailed description of risks and global concerns of the population data, tools and methods toaddress these complex problems in the context of disasters. In particular, a scientific review from(Simon, Goldberg, & Adini, 2015) is based on the use of social media in emergency situations.

In the global perspective of natural hazards and disaster relief, many works emerged to use SMD for their understanding and assessment (Guan & Chen , 2014), detecting greater risks throughpatterns discovery (Niles, Emery, Reagan, Dodds, & Danforth, 2019), or deployed technologies and tools for data mining (Landwehr & Carley, 2014). These tools and platforms have been deeply analysed along with their methodological considerations as important data sources of informationto understand public health issues (Kim, et al., 2013). In this line, one can find a number of taxonomies for data analytics techniques, which are developed along with social sensing and location-based systems (Hamzah & Vu, 2018), as well as reviews of platforms and crowdsourcingtools for disaster management (Poblet, García, & Casanovas, 2013).

In the context of extreme floods and heat waves, the vulnerability of coastal areas has been perceived in several case studies; (Valenzuela, Esteban, & Motoharu, 2020) and (Esteban, et al., 2021). Parallel contributions to address this issue were in the line of generating more structured datasets from historical weather records for coastal flooding (Haigh, et al., 2017) and general trends in flooding (Stevens, Clarke, & Nicholls, 2016). Besides, high-resolution populationdata served to improve estimations of global flood exposure (Smith, et al., 2019). As social mediabecame more popular as a preferred communication channel, the need for effective informative messaging in emergencies became challenging and it was addressed through terse messages in the case study from (Sutton, League, Sellnow, & Sellnow, 2015). Case studies such as the RedRiver Valley Flood Threat relied on Twitter microblogging services, and they considered their implications significant to treat mass emergency events (Palen, Starbird, Vieweg, & Hughes, 2010). Twitter took a similar role along with Facebook as organisational communication platform in flood events in Northern Ireland (Stephenson, Vaganay, Coon, Cameron, & Hewitt, 2018), or Chennai flood towards disaster management (Nair, Ramya, & Sivakumar, 2017), among others. Furthermore, high-resolution social sensing of floods has been shown to produce high-quality historical and real-time maps of floods when observing these types of natural hazards (Arthur, Boulton, Shotton, & Williams, 2018). The fusion of social sensing with remote sensing has recently proved to derive informed flood extent maps via deep learning methods (Sadiq, Akhtar, Imran, & Ofli, 2022). On the other hand, climate change has motivated to mine social media for identifying and tracking the impact of heat waves (Cecinati, Matthews, Natarajan, McCullen, & Coley, 2019), and their response from themes related to air conditioning, cooling center, dehydration, electrical outage, energy assistance and heat (Jung & Uejio, 2017).

At this point, data acquisition and processing remain crucial tasks in almost any analytic tool for SMD. Precisely, in the context of disaster response there is an added need to capture real-timedata, which was analysed from the humanitarian logistics perspective in the research work from (Sokat, Zhou, & Dolinskaya, 2016). Big data tools take a key role in this process, and there is a variety of complex tools available for real-time acquisition such as (Imran, Castillo, & Patrick, AIDR: Artificial Intelligence for Disaster Response, 2014). Real-time stream analytics are widelyused for a diverse of tasks including retrieval, topic classification or clustering (Gupta & Hewett, 2020). Natural language processing of SMD poses multiple challenges. such as learning information categories, which require considerable amounts of annotated data for supervised classification tasks (Imran, Mitra, & Castillo, Twitter as a Lifeline: Human-annotated Twitter Corpora for NLP of Crisis-related Messages, 2016). Moreover, combining semantic information extraction via machine learning techniques (LDA) with spatial and temporal analysis demonstrated to improve disaster management procedures (Resch, Usländer, & Havas, 2018).

In these research areas, there has been a number of works leveraging the use of deep learning methods such as convolutional neural networks to understand crisis-related data (Nguyen,et al., 2016) or extreme flooding events (Romascanu, et al., 2020). The idea of combining recurrent or convolutional neural networks that include an encoder and a decoder as part of the same model was introduced by Google Brain and Google Research with the work from (Vaswani, et al., 2017), and it derived to future extensions of deep bidirectional neural networks that we base for our first step of the analysis in our paper. Besides, semantic compositionality resulted in considerable advances in the sentiment analysis domain through recursive deep models (Socher, et al., 2013) along with other machine learning techniques (Prasad K, 2020), which conducted to applications in SMD such as in the political domain (Alfina, Sigmawaty, Nurhidayati, & Hidayanto, 2017). The emerging evolution of this application domain of SMD analysis brought the scientific communityto address novel tasks such as engagement prediction generally in online social networks (Sadeque & Bethard, 2019), more specifically in the context of disasters (Alshehri , 2019). At this time, novel techniques for fusing AI techniques emerged in the context of disasters (Alam, Ofli, & Imran, Descriptive and visual summaries of disaster events using AI techniques: case studies of Hurricanes Harvey, Irma, and Maria, 2019), and crowdsensing in the specific context of heat waves (Grasso, Crisci, Morabito, Nesi, & Pantaleo, 2017). On the other hand, stochastic AI fundamentals (Sands, 2020) introduce advance topics of deterministic AI that have demonstrated efficacy in a broad set of problems and will potentially benefit the analysis also in the disaster domain.

The rest of this paper is organized as follows. In Methodology section, we describe the design and application of our framework, which contains key components from the literature for the analysis of disaster-related SMD from textual information using machine learning and natural language processing. These components involve deep bidirectional Transformer neural networks for message filtering, inference models, sentiment & behaviour analysis, and a proposed approach to match behavioural indicators with decoded climate variables to analyse thermal comfort. In Data section, we describe the set of collections available and those we use in our analysis, along with the data pre-processing. Then, we present and discuss our extensive qualitative analysis that applies our methodology on the target collections of floods and heat waves. Finally, the last section concludes the paper.

3. Methodology

In this section, we describe the used method to analyse SMD in the domain of disaster responseto assess the quality of SMD, in order to identify relevant messages from authorities, journalists, volunteers or other entities. The schematic diagram of the proposed framework for the methodology of this analysis is shown in Figure 1.

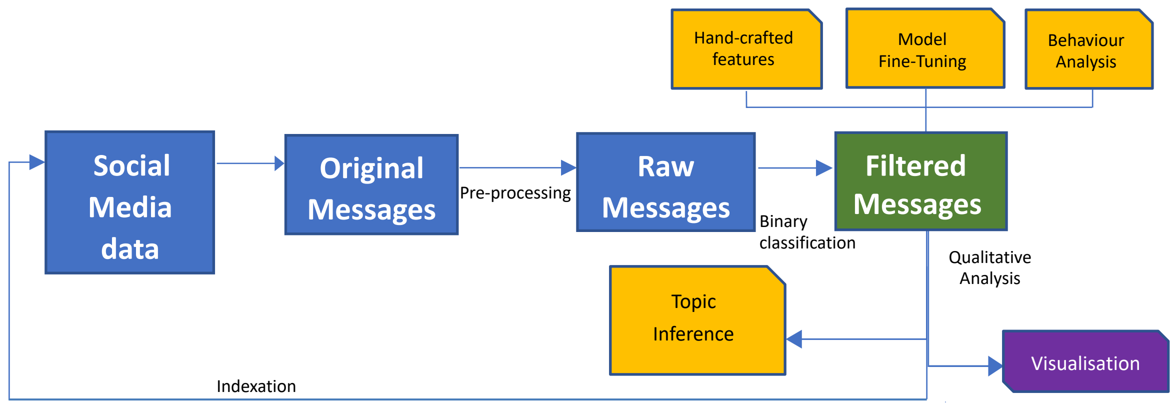

Figure 1. Schematic diagram of the proposed framework for the methodology of the analysis afterpre-processing and filtering messages

First, we pre-process the original messages from SMD collected that are related to disaster response to obtain raw messages.

Next, we apply the models from (Ponce-López & Spataru, 2022) to filter certain messages related to disasters using binary classifiers. These models are based on deep neural networks to train distilled Bidirectional Encoder Representations (BERT) from (Sanh, Debut, Chaumond, & Wolf, 2019) using the Transformers Python library from (Wolf, et al., 2020; Wolf, et al., 2020). Inparticular, we aim to filter disaster-related messages that contain humanitarian and medical information, which include any level of severity. Besides, we use a sentiment analysis classifier ofanother pretrained model from (Wolf, et al., 2020) to filter positive messages. The indexes obtainedfrom the classification allow both to identify the filtered messages in the data corpus for the nextsteps and to recover any information from the original messages.

The following sections describe the processes for learning subsequent topics models from filtered messages, identifying behavioural indicators and matching this information with climate variablesof thermal comfort.

4. Topic Inference and Category Refinement

We describe the method we use to discover abstract topics that occur in our filtered data collectionsfrom their text using statistical modelling and, in particular, the Latent Dirichlet Allocation (LDA) method from (Blei, Ng, & Jordan, 2003). This method allows learning models from a corpus vocabulary to identify terms and subsequently classify messages into particular topics. Each topic consists of a set of words that are modelled as Dirichlet distributions (Rehurek & Sojka, 2010).

The data pre-processing for this procedure involves tokenisation, removing short words and stopwords, lemmatisation of words into the first person and verbs into the present, and stemmisation of words into their root form. Once the data is pre-processed, we create a Bag-of-Words (BoW) containing the number of times a word appears in the set using Gensim (Rehurek & Sojka, 2010). We filter out tokens that appear either in less than 15 messages or in more than 0.5messages as a fraction of the total corpus. Then, we keep only the first 100,000 most frequent tokensand we create a dictionary with the number of words and number of times those words appear. We use this dictionary to create LDA topic models from both Bag of Words (BoW) and Term Frequency Inverse Document Frequency (TF-IDF) to explore the words occurring in each topic and theirrelative weight. Once a topic model is learned, we can use a test message to calculate the highestprobability (classification accuracy) of the message, in order to be a part of the topic that the model assigned.On the other hand, we subsequently use CrisisDPS from (Alam, Muhammad, & Ferda, CrisisDPS: Crisis Data Processing Services, 2019) to provide a refined categorization to match the above topics. This system was developed to support humanitarian aid tasks automatically as integration into disaster response workflows. The usage of this service takes input textual messages (e.g. our filtered messages from data collections) to determine for every message: the type of disaster; whether it is informative or not, and what type of humanitarian information it contains, using machine learning classifiers.

5. Text Analyisis and User's Behavioural Indicators

Our qualitative analysis focuses on the filtered messages from both data collections of floods andheat waves.

From the number of tools available for text analysis, we find the usage of ParallelDots framework and their API functionalities from (Paralleldots, 2020) a proper fit to automatically identify the frequency and dominance of a variety of behavioural indicators in relevant messages. Thistool utilizes models pretrained with machine learning techniques from (Jain, Aggarwal, & Singh, 2019) for the recognition of the well-known basic emotions from (Ekman, 1992) and (Plutchik &Kellerman, 1980). Although further details about the machine learning models are not provided in the system ́s API documentation, we describe the list of five behavioural indicators and their confidence scores provided as category values which we consider in our analysis:

- **Sentiment:** negative, neutral, or positive. It describes the process of systematically identify,extract, quantify and study affective states and subjective information.
- **Emotions:** angry, excited, bored, fear, happy, or sad. It works at the sentence level to extractwords and phrases representing emotions or emotive states.
- **Intent**: feedback, marketing, news, query, or spam. It describes the type of information toidentify genuine tweets and understand users' intentions.
- **Abuse**: abusive, hate speech, or neither. It focuses on filtering abusive content from a textcorpus based on revealing connotation terms.
- **Sarcasm**: non-sarcastic, or sarcastic. It focuses on capturing components in a text block that aim to mock or convey contempt.

The system can be used either under a specific subscription or for free, having a limited number ofdaily hits that are reset over the month. Every hit is defined as the execution of a target query message to be analysed. We use the free basic version using as input queries our reduced set of filtered messages resulting from the deep binary classifiers. Further details about the usage of theframework are provided along with the code documentation.

Besides the behavioural indicators, which we found of high value for our purpose in this research domain, the framework allows us to recognise predefined and custom categories that are also relevant for our qualitative analysis. The predefined categories rely on the content taxonomy of IAB categories from (IAB Tech Lab, 2022). This taxonomy is an industry standard containing levels of categories that are widely used in services like advertising, Internet security and filtering appliances. Finally, the system allows the users to define custom categories for the messages to be classified, even though the authors do not provide further specifications about this unsupervised or semi-supervised machine learning functionality.

In the context of disasters, we base these custom categories following advice from the National Governors Association (NGA & ASTHO, 2020) and the Economic Development Administration (EDA & IEDC, 2020), to define a set of categories related to the phases of a disaster:

- **Prevention** or Awareness: preventing human hazards from natural and man-made disasters.
- **Mitigation**: reducing loss of life and property by lessening the impact of disasters and emergencies.
- **Preparedness**: the continuous cycle of planning and organising.
- **Response**: the coordination and management of resources.
- **Recovery**: restoring critical functions to the community.

Due to the nature of messages in our data collections, we break down the recovery evaluationphase into needs and essentials for the purposes of resource allocation for our custom categorisation.

In the context of disaster response, governance of disaster risk reduction and resilience for sustainable development, we develop a list of potential stakeholders from a variety of sources available online related to this domain. These refer to national and sub-national public authorities,public authorities, category responders, sector resilience leads, non-governmental organisations, and civil society organisations. We look for Twitter accounts for this list of users aiming to performa semi-automatic identification of key messages and relevant usernames that might be first overlooked by the filtering approach. This allows to feedback the system by including new potential key messages from these users that are re-considered in the system with a reasonable effort of manual user inputs. By identifying these missing governmental and non-governmental institutions and other accounts in social media, we complement the behavioural analysis along with additional interactions of users to new key messages in terms of their reactions, responses and forwarding (retweets).

6. Climate Variables of Thermal Comfort

We describe the procedure developed to decodify weather data encoded by meteorological stationsinto synoptic observations (SYNOP records) freely provided by the U.S. National Oceanic and Atmospheric Administration (NOAA, 2022). The goals of this decodification process are two-sided. First, to reveal climate variables that are not yet available in annual reports from official sources such as the UK Meteorological Office (metoffice, 2022). Secondly, to obtain more detailed information directly from weather stations without having been yet processed to generatethe summaries for global human-readable weather reports.

We base on the six basic factors defined by the Health and Safety Executive (HSE, 2020) to retrieve climate variables. Climate variables are related to thermal comfort, which is described by the HSE as a person's state of mind in terms of whether they feel too hot or too cold. Moreover, the level of thermal comfort is influenced by a combination of environmental, personal and work-relatedfactors. From these six basic factors, we aim to decode SYNOP weather data records for extractingthe following human-readable climate variables and measurable units:

- Wind Speed (Knot (KT) converted to km/h).
- Maximum temperature (℃).
- Average temperature (℃).
- Relative Humidity.
- Precipitation (mm).
- Pressure (hPa).

Therefore, in Algorithm 1 we present the pseudocode of this decoding approach. First, SYNOP weather records are collected via queries in the OGIMET system from (Ballester Valor & García López, 2022), then the decoding functions are based on (metaf2xml, 2020), which consistsof a combination of scripting language functions in PERL and XML parsing for decoding a varietyof reports, including synoptic observations. Further information about this procedure and form of SYNOP messages are provided along with the code documentation.

Algorithm 1: Pseudocode for Decoding SYNOP Weather Records

Input	:	Encoded SYNOP Document, $\boldsymbol{D}$
Output	:	Decoded data frame of climate variables, $\boldsymbol{DF}$
Step 1	:	Read SYNOP document, $\boldsymbol{D}$
Step 2	:	Initialize empty data frame, $DF \leftarrow DataFrame()$
Step 3	:	Initialize empty lists for each climate variable 'wind speed', 'max temperature', 'average air temperature', 'relative humidity', 'rainfall', and 'pressure'. $\boldsymbol{CV} \leftarrow \{ws, mt, at, rh, rf, pr \leftarrow list(), list(), list(), list(), list(), list()\}$
Step 4	:	**for** each decoded message $\boldsymbol{m}$ **in** $\boldsymbol{D}$ **do**
Step 5	:	Apply weather report PERL parser to generate decoded XML, $\boldsymbol{doc} \leftarrow metaf2xml(\boldsymbol{m})$
Step 6	:	Get XML elements by decoded tag names for each target climate variable andappend their values in the lists, $\boldsymbol{CV} \leftarrow \{ws \leftarrow getWSvalue(\boldsymbol{doc}['wind']['speed']),$ $mt \leftarrow getMTvalue(\boldsymbol{doc}['temp']['max']),$ $at \leftarrow getATvalue(\boldsymbol{doc}['air']['temp']),$ $rh \leftarrow getRHvalue(\boldsymbol{doc}['relHumid']),$ $rf \leftarrow getRFvalue(\boldsymbol{doc}['precipitatio\boldsymbol{n}']['precipAmoun\boldsymbol{t}']),$ $pr \leftarrow getPRvalue(\boldsymbol{doc}['stationPressur\boldsymbol{e}']['pressur\boldsymbol{e}'])\}$
Step 7	:	**end for**
Step 8	:	Dump set of values for every climate variable into a data frame, $\boldsymbol{DF} \leftarrow \{\boldsymbol{CV}[\boldsymbol{var}]\ for\ \boldsymbol{var}\ in\ CV\ targets\}$
Step 9	:	**return** $\boldsymbol{DF}$

We perform climate variable extraction using the steps described above on our target data collections described in the following section about data description. Extracting climate variableswithin the same periods of time as our SMD collections allows us to synchronise them withthe previous behavioural indicators to provide combined insights for thermal comfort.

7. Data

This section presents a list of different data collections related to disasters, which have been captured during the years 2020 and 2021. Then, we present our general pre-processing methodology of our SMD collected for text standardization into raw input text for the machine learning classifiers.

8. Collections

We describe different collection captured from Twitter SMD using the AIDR tool from (Imran, Castillo, & Patrick, AIDR: Artificial Intelligence for Disaster Response, 2014). The data have been collected for a number of different disaster events, including floods, heat waves, ice and snow, storms, and hurricanes. The different data collections are described in Table 1, including their periods of time and the main parameters included in the AIDR system settings.

Table 1. Description Of Smd Collections Related To Disasters Collected In 2020 And 2021

Type of Event	Location	Period of Time	No # Tweets	List of Search Keywords
Floods	**UK**	**November 2020**	**27K**	*UK flood, UK rainfall, Britain flood, Britain weather, extreme rainfall, London weather, London flood, flood warning, severe flood, severe rainfall, water hazard, flood hazard, hazard UK, flood day, flood alert*
Heatwaves	**UK**	**Jun-Jul. '20** **Jul-Aug. '20** **Aug-Sep. '20**	**602,5K**	*UK heatwave, UK hot weather, Britain weather, Britain heatwave, London weather, London heatwave, hottest day UK, Britain hottest day, summer hottest day, +30C, extreme heat, heatwave thresholds*
Hurricane Isaias	US	July 2020 August 20	217K	*hurricane Isaias, Isaias Florida, flooding Florida, storm surge Florida, heavy rain Florida, coastal flooding Florida, flooding FL, storm surge FL, heavy rain FL, coastal flooding FL, hurricane Isaias FL, FLWX, hurricane FL, hurricane Florida, Isaias FL, Isaias Miami, Isaias North Carolina, hurricane Isaias NC, flooding North Carolina, flooding NC, storm surge North Carolina, storm surge NC, heavy rain North Carolina, heavy rain NC, coastal flooding North Carolina, coastal flooding NC, Isaias NC, Isaias North Carolina, hurricane NC, hurricane North Carolina, Isaias*

				Raleigh, Isaias Charlotte, Wilmington NC, hurricane Isaias NC, storm surge NC, Isaias
				Wilmington NC, Oak island flooding NC, Oak island NC, Oak island Isaias
Storm Christopher	UK	January 2021	54K	*Storm Christoph, UK storm, Storm England, storm Ireland, storm Scotland, UK flood, UK rainfall, Britain flood, Britain weather, extreme rainfall, London weather, London flood, flood warning, severe flood, severe rainfall, water hazard, heavy rainfall, heavy rain, flood hazard, hazard UK, flood day, flood alert, strong winds, strong wind*
Snow and Ice	UK	February 2021	668K	*UK snow, UK ice, snow England, ice Scotland, snow Scotland, ice Wales, snow Wales, UK flood, snow alert, ice alert, ice warning, snow warning, UK rainfall, Britain flood, Britain weather, extreme rainfall, London weather, Scotland weather, Wales weather, flood warning, severe rainfall, water hazard, ice hazard, snow hazard, heavy rainfall, heavy rain, flood hazard, hazard UK, flood day, flood alert*
Heatwaves	UK	June 2021 July 2021 Sep. '21	21M	*UK heatwave, UK hot weather, Britain weather, Britain heatwave, London weather, London heatwave, hottest day UK, Britain hottest day, summer hottest day, summer, temperatures, British summer, British temperatures, +30C, extreme heat, heatwave thresholds*

For simplicity, in our qualitative analysis for this pilot study, we focus on the data collected in the UK during 2020 for floods and heat waves. These two first data collections provide us with a considerable amount of data. Both aim to feed the deep learning classifiers at the filtering stage and to subsequently apply machine learning classifiers, in order to obtain the main insights of our overall analysis methodology described previously. We plan to improve the remaining data collections and get further insights in future analysis.

9. Text Pre-Processing

As mentioned first in the methodology section, we use a similar methodology from (Ponce- López & Spataru, 2022) for text pre-processing from original messages in all our data collections.We use the Twitter pre-processing library from (Özcan, 2020) for cleaning mentions, hashtags, smileys, emojis, or reserved words such as RT. Then, we follow up the pre-processing with the

BS4 library from (Richardson, 2021) to parse HTML URLs, and regular expression (Friedl, 2009)operations in Python to remove anything that is not a letter or a number in all the messages. The result is standardized raw text messages that are recognized both at the filtering step and the following stages of the presented methodology.

10. Qualitative Analysis

This section describes key results and insights from a qualitative analysis in our two main data collected for UK in 2020 with the AIDR tool for floods and heat waves. First, we explain our results related to frequent terms and relevant keywords for message filtering, identified topics, sentiment analysis and category refinement. Next, we present results of text analysis and identification of several behavioural indicators. Finally, we show the procedure of matching thosebehavioural indicators with decoded climate variables related to thermal comfort.

11. Message Filtering, Topic Inference, and Sentiment Analysis

For the first part of our visualisation module, we use the Python Wordcloud library and their APIfunctionalities from (Mueller, 2020) to generate visual interpretations of the most frequent terms and words sorted by number of occurrences.

These functionalities are applied to the raw text obtained from the pre-processed data collections of UK floods and heat waves in 2020, which are shown in Figure 2 and Figure 3. Thefirst noticeable aspect of our qualitative analysis is that the most frequent terms identified in thesedata collections reveal information related to weather warnings in the context of floods, as well asglobal climate warming and activism in the case of heat waves.

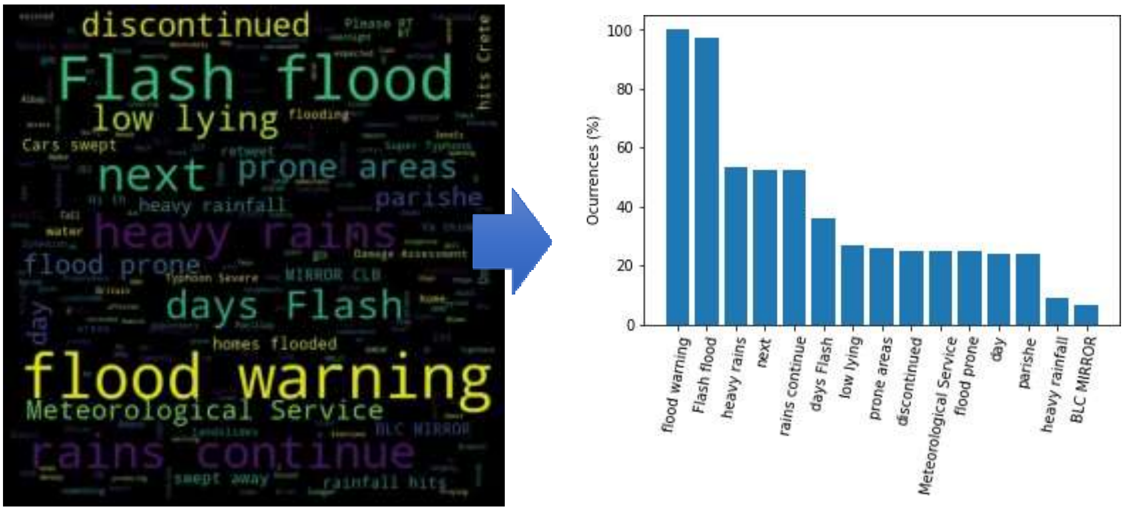

Figure 2. Word cloud chart and key terms plot in UK Floods 2020. 'Flood warning' and 'Flashflood' appear to be the most frequent words, followed respectively by the words 'heavy rains'and other terms related to the context of floods and weather

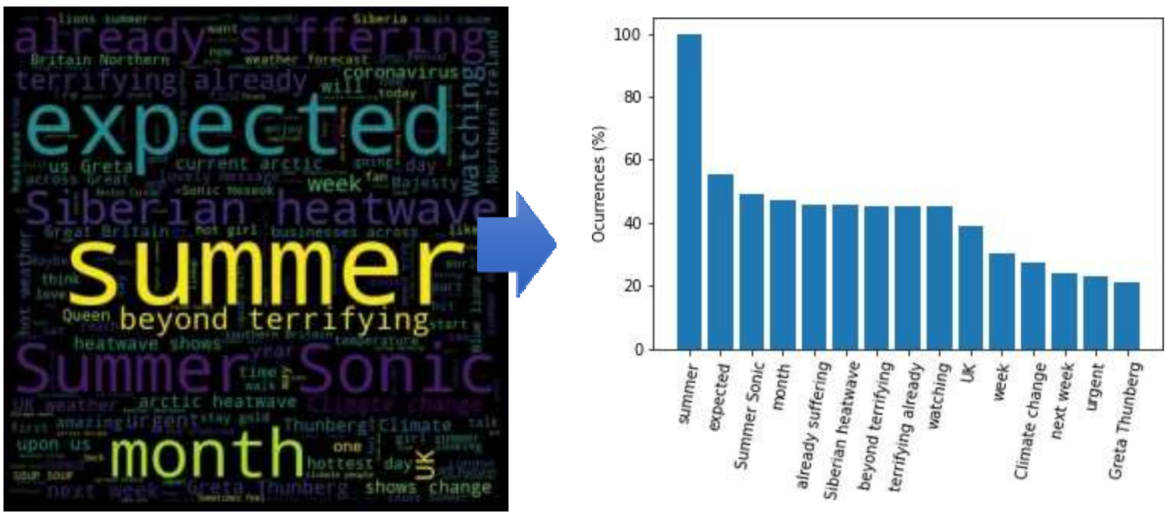

Figure 3. Word cloud chart and key terms plot in UK Heatwaves 2020. 'Summer' appears to be the most frequent word. Some other words related to activism and policies were identified in thecontext of global climate

Moreover, the deep learning classifiers detected about 24K messages related to disasters out ofthe whole data for floods, which is a considerable amount with respect to the total number of collected messages. In the case of heat waves, about 91K out of a total subset of 100K messages from the data were considered to be related to disasters. The representation of the main categories

related to disasters is shown in Figure 4. For floods, we identified 1,098 medical-related messagesand 275 related to humanitarian standards, while in the case of floods we identified 26,285 medical-related messages and 1,421 related to human standards.

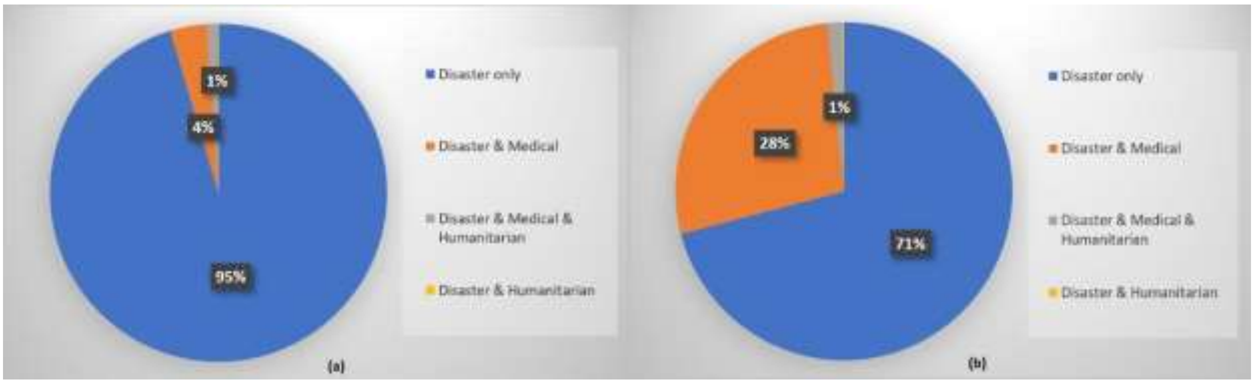

Figure 4. Percentage distribution of filtered messages for Floods (a) and Heatwaves (b) by main disaster categories: humanitarian standards and medical-related information

Then, we applied LDA-based topic inference models to the messages likely related to disasters.

In the case of floods, the most frequent terms found by the system were 'warn', 'river, 'flash', 'water', 'hazard', and 'novemb', sorted respectively by descending relevance order. These terms gave us hints about potential topics related to informative weather messages or about warnings related to specific flooding events happening or going to happen. Other composite terms or keywords considered important were 'flood warning', 'flash flood', 'continues flood', and 'FloodAlert'. Many of those refer to informative messages from official local news and related sources. Besides, the dictionary of most frequent terms revealed words such as 'flood', 'detail', 'fair', 'form', ' 'fund', which appeared to be related to flooding events their correlation with Covid-19 deathsor vulnerable areas, as well as to political decisions. Finally, the topic inference classifiers weighted again terms such as 'novemb', 'flash', 'warn', 'river', 'issue', 'till', which were related to official reports and information on the duration and location of the flooding events.

The sentiment analysis classifier identified 5,871 positive messages out of the 27,096 tweets. As shown in Figure 5, the tweets were generally more positive around early afternoon and after midnight. An influencing factor of this was the increased activity at these hours, especially duringthe rainiest & active days, between 3 pm on the 11th November and 2 am on the 13th November2020. The overall hourly activity of users, however, appeared to be distributed differently along the whole period of 10 days of collected data. When we focus on the filtered messages, the positiveness of messages is around 17% (4,190 tweets), 27% (293 tweets) and 16% (45 tweets) for the disaster, disaster & medical and disaster & humanitarian related messages, respectively. Although many messages are from official sources, these low percentages of positiveness suggestthat there was a considerable amount of messages with negative connotations and a high influenceof messages coming from other external sources. To dig into this issue, these signals indicate a potential need of increasing the amount of positive informative messages coming from official sources, in order to alleviate the negative effects of these events.

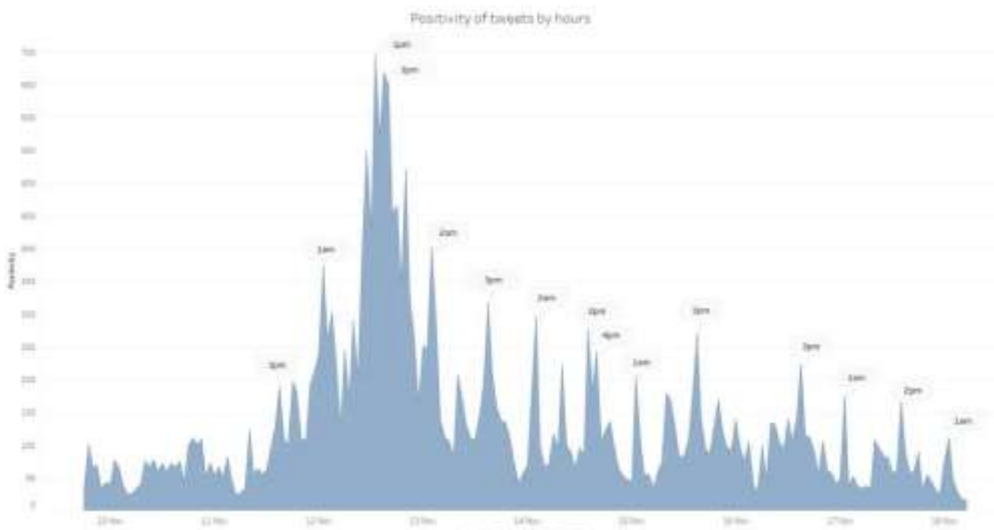

Figure 5. Sentiment analysis in the UK Floods data collection

For heat waves, the most frequent terms found in the collection subset were 'heat', 'extrem', 'forget', 'year', 'record', 'weather', and 'drought', sorted respectively by descending relevant order. These terms gave us again hints about potential topics related to informative weather messages, but also about climate conditions and warnings related to events. Other composite termsor keywords considered important were 'fire fighter', 'extreme heat', 'climate change', 'heat ray', or 'threat'. Many of those refer to retweets from scientists about warnings related to extreme weather conditions increasing threats to property and life. Besides, the dictionary of most frequent terms revealed words such as 'decid', 'money', 'polic', 'fact', 'figther', 'fund', which appear to be related to political decisions or requests from activists related to the disaster response. Finally,the topic inference classifiers weight terms, such as 'resourc', 'lack', 'fund', 'figther', 'fact', 'year', which are related to claims for action in climate change and global warming.

The sentiment analysis classifier identified 31,467 positive messages out of the 99,967 tweets. As shown in Figure 6, the tweets were generally more positive in the evening with a few exceptions during some early morning and afternoon. An influencing factor of this was the increased activity in the evening, especially on the 26th of August. The overall hourly activity of users, however, appeared to be distributed differently during this period of time. When we focus on the filtered messages, the positiveness of messages remains low around 8% (7,415 tweets), 1% (307 tweets) and 7% (107 tweets) for the disaster, disaster & medical and disaster & humanitarian related messages, respectively. Again, this low positivity suggests that many messages were coming from non-official sources having plenty of negative connotations and barely telling anything informative or valuable to the public. Again, to alleviate this effect along with an increased positivity of informative messages from official sources, another classification layer for informativeness would be helpful for categorisation.

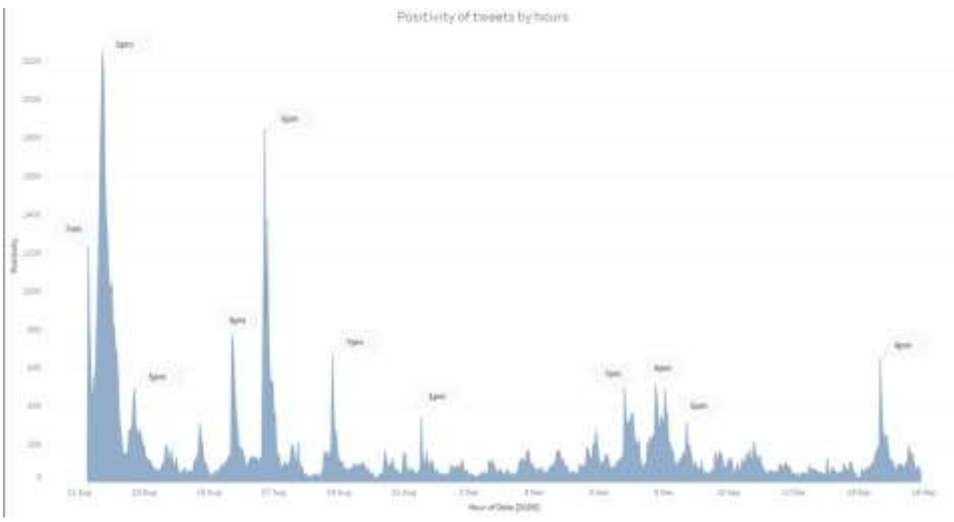

Figure 6. Sentiment analysis in the UK Heatwaves data collection

From the all set of positive filtered messages of the heat wave data collection, we end up with a total of 70 tweets that appear to contain information related to three main information categories: disasters, medical, and humanitarian standards. As a result of applying CrisisDPS using as input for these filtered messages, the pie charts shown below in Figure 7 illustrate a summary of tweets falling into different types of disaster and crisis, as well as revealing their informativeness and typeof humanitarian information. Still, we can notice a considerable amount of non-informative messages up to almost half of them, and the type of disaster related to fire matches withthe composite terms detected by our topic inference models. We highlight the usability ofcombining these methods from the identification of topics to a refined categorisation for focused disaster response.

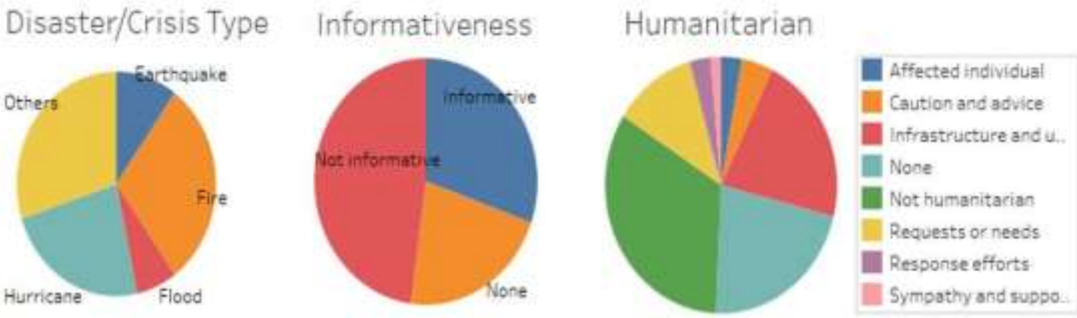

Figure 7. Sub-categorisation refinement for filtered messages from UK Heatwaves using CrisisDPS *(Alam, Muhammad, & Ferda, CrisisDPS: Crisis Data Processing Services, 2019)*

12. Text Behavioural Analysis

Here, we present the results of applying analysis of behavioural indicators described in themethodology, including both predefined and custom categories related to the phases of a disaster.First, we conduct the analysis on the 36 resulting messages from filtering the UK floods data collection with our combination of deep binary classifiers presented previously. Figure 8 shows the results for the main IAB predefined categories (a) and custom categories broken down into 441 detailed phases of a disaster (b). For the IAB taxonomy (a), we can notice the dominant categories 442 are worldpost, green and impact, respectively, followed by entertainment and politics. Given the reduced number of filtered messages, we can show detailed results on this data collection for eachmessage maintaining simplicity in the visualisation. The key filtered messages are related toreactions to the recent hurricanes, heavy winds, and storms, as well as news about flood warnings, alerts and the status of rivers. Most of these messages fall into the 'impact' category which is the mostrelevant category in the context of disaster response. Nevertheless, most messages from the 'politics' and 'entertainment' categories reveal recent actions or active discussions about political decisions and their consequences after the flooding event. There is almost no influence from the categories 'Crime', 'Religion', and 'Taste', for disaster-related messages. In the case of custom disaster categories (b), we can notice a predominance of the prior phases 'Preparedness', 'Mitigation', and 'Awareness', related to messages which are sent some days, hours, or minutes before a certain event happened. These messages are sent mostly from accounts related to news and meteorological services. For the posterior phases of a disaster, there is also a significant influence of 'Response' messages. However, in this case they are mostly related to reactions of people after the event when everything returned to normality. By contrast, the lesser confidence scores are obtained by the 'Need' category as part of the 'Recovery' phase. Although this is expected given the low severity of these events did not cause major trouble, there is a considerable presence of messages related to the category 'Eseential' which refer to resource allocation.

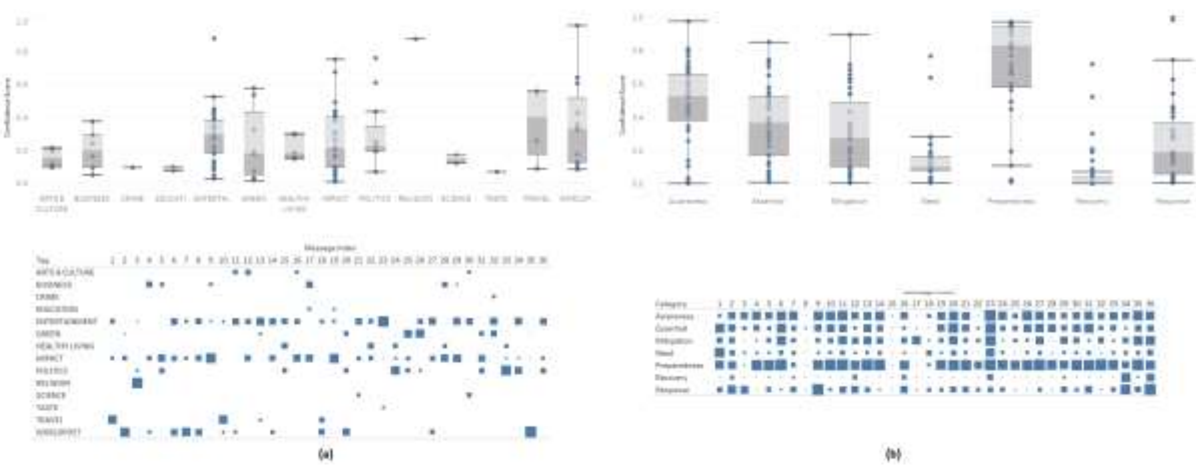

Figure 8. Distribution of averaged confidence scores and dominances of the main IAB categories for filtered messages of (a) Floods and (b) Heatwaves data collections in the UK. At the bottom, each column represents a filtered message assigned to each category, and the size of the squares represents the confidence score for that message in that category (the higher the score the bigger the square)

With regard to the behavioural indicators, in this case, we conducted the analysis on filtered messages in both data collections. Figure 9 and Figure 10 show the results of the averaged distributions of dominance for each behavioural indicator. The distributions are pretty similar on both datasets, and the behaviour indicator that appears to be the most equally distributed in its values of confidence scores is the 'sentiment'. The 'sarcasm' and 'abuse' indicators also behave similarly on both datasets, with a significant amount of up to almost 40% of messages considered sarcastic and a slightly increased number of abusive messages in the case of floods. Although both collections show, as expected, a predominance of news in their 'intent' indicator, it is surprising to see the increased amount of filtered messages that are still considered as 'spam' in the heatwaves collection. This phenomenon is likely to be caused by the higher number of total messages in this collection. We can also see an increased number of filtered messages classified as 'feedback' to the floods collection. Lastly, the main relevant differences in terms of behavioural analysis when comparing both collections are in the 'emotion' indicator, where wecan notice a significant increment of angry messages in the floods collection, increased levels of fear and sad messages in the heat wave messages, but also in the exciting messages. Although these are surprising outcomes at a first glance, by digging into the heatwave collection we discover many messages related to global warming and activism, which are generally found to be those messages triggering the score levels on these three indicators.

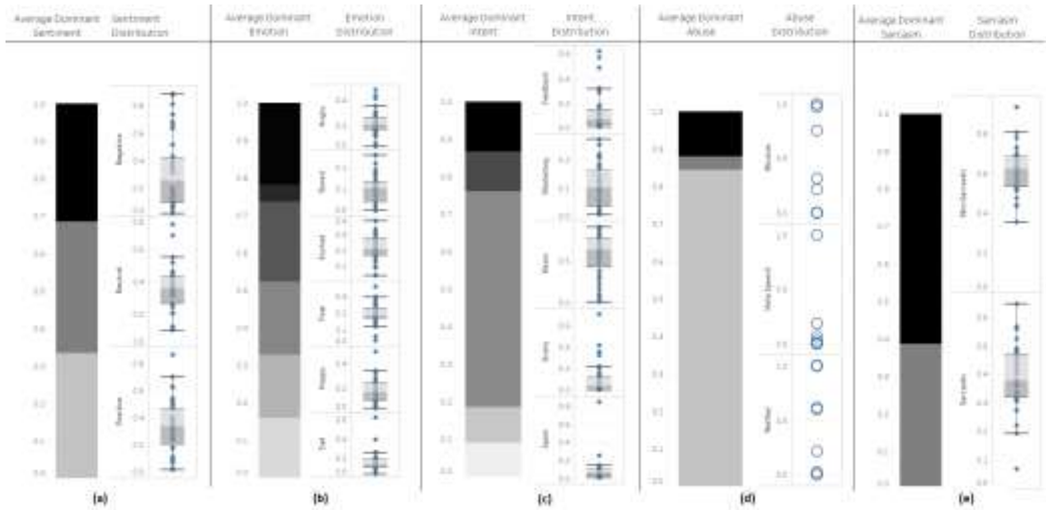

Figure 9. Average distributions of dominances for each behavioural indicators: sentiment (a), emotion (b), intent (c), abuse (d), and sarcasm (e), on filtered messages of the UK Floods collection

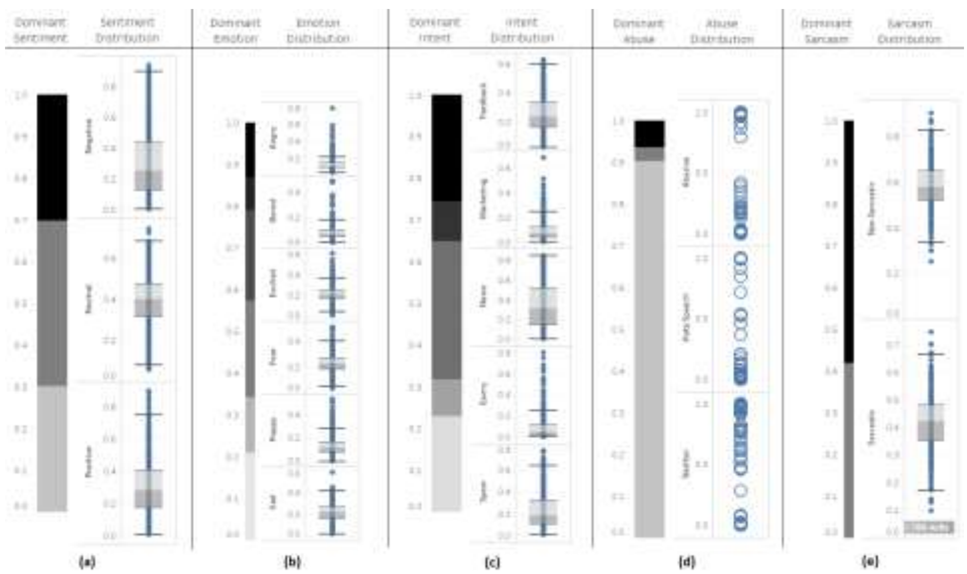

Figure 10. Average distributions of dominances for each behavioural indicators: sentiment (a), emotion (b), intent (c), abuse (d), and sarcasm (e), on filtered messages of the UK Heatwaves collection

Moreover, we conducted a comparative analysis of key messages both from users' accounts thatare manually added from our list of well-known sources of information and those key messages that are detected via automatically filtering approach. From the list of known users described in the methodology, in the heatwave collection, we found the highest occurrence of messages mostlycoming mostly from national public authorities, such as official meteorological services, health and social care, and NHS; but also a considerable amount from well-known independent meteorologists and the scientific community in climate-related fields. These last two were almostat a similar level of occurrences than national public authorities.

On the other hand, the automatic filtering approach offers the possibility of discovering new potential candidates from the initial diversification of new information sources that become morepopular in the network over time, and whose reliability is worth being further evaluated to

eventually include their knowledge, contributions, and value as a new relevant source of official information. This combined approach helped us to discover major contributions of each independent process to eventually become a semi-automatic approach to feedback on the whole system and better support responders in focusing on relevant information.

In conclusion, we found that a trade-off between sources of relevant information coming both from governmental institutions and those from non-governmental institutions can complement each other to enrich public knowledge and informativeness. Although this combination becomescrucial nowadays, it needs proper evaluation of reliability for new potential candidates to minimisemisinformation, which is a field that remains out of scope for this paper.

12. Matching Behaviour with Thermal Comfort

We introduce a novel qualitative analysis with explanatory visualisations which combine textualanalysis and behavioural indicators with the climate variables related to thermal comfort that we obtain with the decoding procedure presented in the end of the methodology section. We conductthis analysis in both entire collections of heat waves and floods in the UK during summer and winter in 2020, respectively.

Figure 11 illustrates a graphic where all plots are aligned to the same points in time. Starting from the top, the first and second plots show the count of positive messages and total activity messages, respectively, in the same way as explained first in this section for the sentiment analysis.Then, according to our methodology, we show values of average air temperatures, maximum temperatures, precipitation, pressure, relative humidity, and windspeed, respectively. Note the missing values for maximum temperatures and precipitation level; they matches exactly with the capturing timescales of the weather stations, which are once per day in the case of maximum temperatures and a few times per day split into the same range of hours in the case of precipitation levels. In addition, note when some value is missing in any variable at a specific time, that point is removed for all variables to allow proper alignment and make the overall synchronisationconsistent. Having pointed that, an aspect to highlight is the clear appreciation of increased levelsof both precipitation and windspeed on the 11th November, followed by a considerably increased activity and positivity levels on the day after and when these weather conditions ceased. Since there are no significant changes on the other climate variables, these increased levels potentially show ageneral improved level of thermal comfort as a consequence of a diverse of triggers. For example,the relief that may occur a few hours after that flooding events ended taking place around differentparts of the country. These specific events caused minor disruptions in terms of response and recovery in this case, and those increased levels of activity and positivity could be caused by multiple factors. Nevertheless, these periods of time, when it is likely to spot moments and delaysfor certain generalised reactions to appear, are significant and sensible aspects to consider in disaster phases, especially for events that could potentially cause major disruptions.

Figure 11. Levels of positive sentiment and user's activity along with climate variables on the UK Floodsdata collection during winter 2020

Figure 12 shows a similar illustration as explained recently in Figure 11, in this case for the heatwaves collection. On the top, however, we plot the levels for each emotional indicators in alignment with user's activity and the set of climate variables. Another consideration is the division into three different episodes of heat waves during the summer 2020; the first during June-July, the second during July-August and the final heat wave during August-September. We can appreciate increased maximum temperatures between 23rd and 25th June of up to 33,4 ℃, which appear to be linked with increased agitation, user's activity and level of boredom. Potentially, this would indicate reduced thermal comfort levels causedby the heat wave. Once temperatures ceased, however, we notice another peak in user's activity on the 30th June. Similarly, the period the from the 30th July to 2nd August shows a similar phenomenon with clear correlations. In addition, we can appreciate increased levels of increased anger with temperatures reaching up to 37 ℃ in few parts of the country on the 31st July. Moreover, we notice some other isolated peaks on emotions related to anger and boredom, which refer to a few outliers from repeated messages. In the last period, however, we can confirm a clear correlation between user's activity, high temperatures and some peaks of boredom and anger, which are repeated at the end of this last period too. These correlations are especially noticeable between 10th-12th August, 18th-21st August, and slightly between 7th-9th and 13th-15th September.

In general, we expose the advantages of aligning behavioural indicators along with climate variables to provide additional valuable information to be considered especially in different phases of a disaster, and applying to episodes of extreme weather conditions to analyse general thermal comfort levels in a population from SMD inputs. Nonetheless, this experimental study shows the application in the pilot study. Influencing factors of thermal comfort are highly diverse, and therefore, a specific domain should require further evaluation.

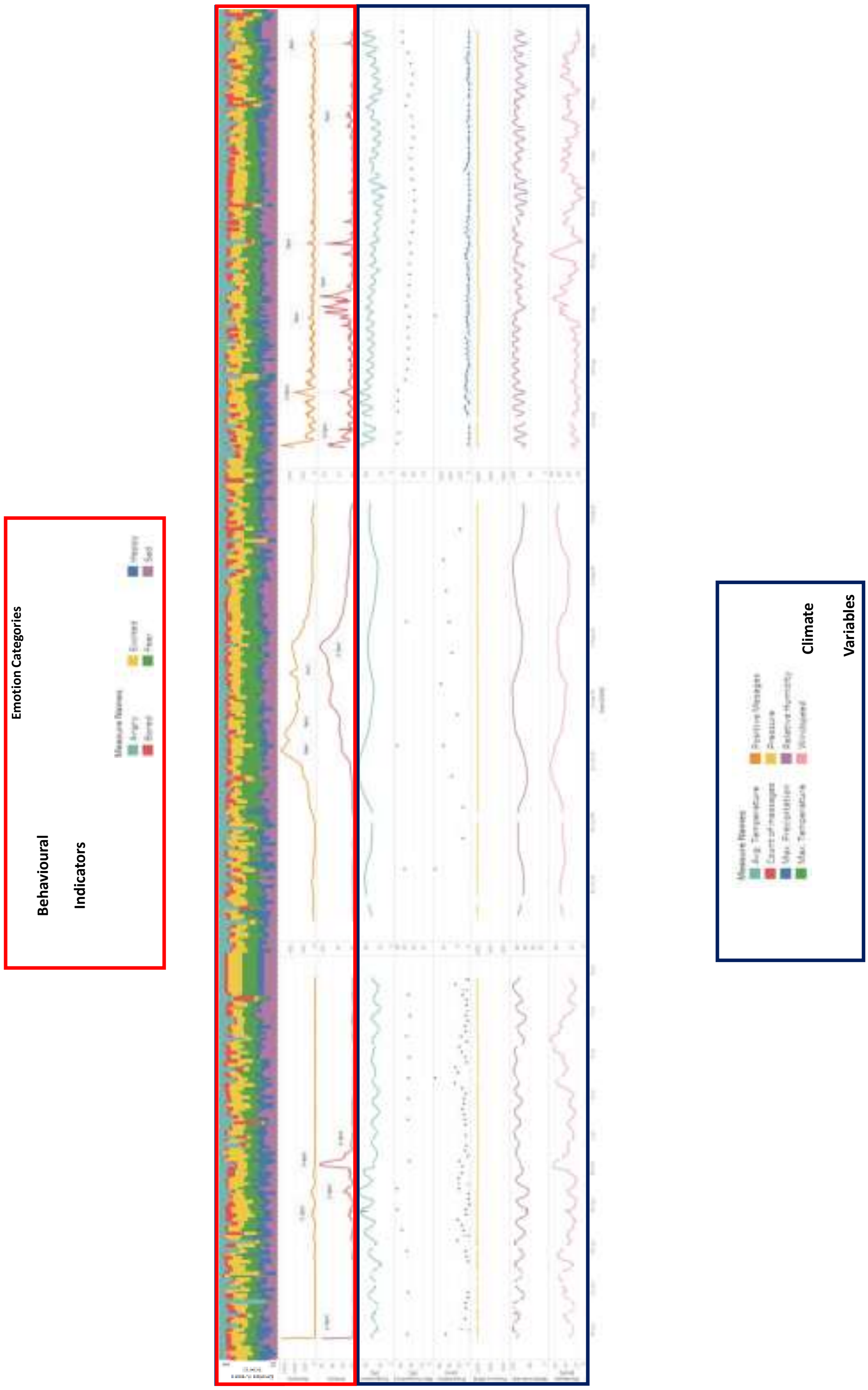

Figure 13. Levels of emotion and user's activity along with climate variables on the UK Heatwaves collection in three different periods of time during summer 2020

13. Conclusion

This research work focused on the qualitative analysis of social media data from disaster-related collections of floods and heatwaves. We use a methodology framework based on a combination of several AI modules. The results of our analysis show novel insights in terms of using approaches to 1) filter disaster-related messages using deep bidirectional Transformer models, 2) learn topic inference models and refine categorization through additional machine learning classifiers, 3) perform sentiment and behaviour analysis, and 4) match behavioural indicators with decoded climate variables from synoptical records to analyse thermal comfort. We also provide a semi-automatic method to discover key messages from user accounts to feedback on the system.

Future work on the side of behaviour indicators will involve a detailed analysis of reactions to messages. These reactions have to do with taking into account likes, taking into account occurrences of forwarded messages (retweets), text analysis of responses to relevant messages as potential new behavioural indicators, among other types of reactions and engagement prediction factors to be included in the qualitative analysis. Indeed, deterministic AI techniques will provide a potential alternative to complement the analysis in the future works. Finally, further validation strategies through quantified methods on the domain-specific influencing factors of thermal comfort will steer the use of behavioural indicators along with climate variables and provide better reliability through novel evaluations in the context of crisis and disaster response.

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