City Research Online

City, University of London Institutional Repository

Citation: Dunkel, A., Andrienko, G., Andrienko, N., Burghardt, D., Hauthal, E. & Purves, R. (2019). A conceptual framework for studying collective reactions to events in location-based social media. International Journal of Geographical Information Science, 33(4), pp. 780-804. doi: 10.1080/13658816.2018.1546390

This is the accepted version of the paper.

This version of the publication may differ from the final published version.

Permanent repository link: https://openaccess.city.ac.uk/id/eprint/21218/

Link to published version: https://doi.org/10.1080/13658816.2018.1546390

Copyright: City Research Online aims to make research outputs of City, University of London available to a wider audience. Copyright and Moral Rights remain with the author(s) and/or copyright holders. URLs from City Research Online may be freely distributed and linked to.

Reuse: Copies of full items can be used for personal research or study, educational, or not-for-profit purposes without prior permission or charge. Provided that the authors, title and full bibliographic details are credited, a hyperlink and/or URL is given for the original metadata page and the content is not changed in any way.

City Research Online: http://openaccess.city.ac.uk/ publications@city.ac.uk

A conceptual framework for studying collective reactions to events in location-based social media

1 Introduction

Events are one of the core concepts of spatial information proposed by Kuhn (2012), and their study, often in the form of social media has become increasingly popular in GIScience (e.g. Sui and Goodchild 2011). However, current work often ignores the distinction between an *event*, with a physical manifestation representing some form of change, and thus being bounded in time (and space), and *reactions* to such an event broadcast in location-based social media (LBSM). Crucially, while events and reactions share attributes, which is why any reaction on social media can also be treated as an event, specific characteristics only apply to reactions. We therefore set out to address this gap, by exploring the relationship between, and implications of explicitly modelling, reactions and events in LBSM. Our paper has the following aims:

i) To develop a conceptual model of reactions to events in location based social media which reflects both interdependencies between reactions and events, and also differentiates between the properties of reactions and events.

ii) To demonstrate, through an implementation, how the conceptual model can be applied in real analysis tasks of reactions to natural and social events

In the following we first briefly review the literature exploring reactions to events in LBSM and ways of characterising context. Based on this review, we then introduce our conceptual model which aims to integrate reactions and events, starting from the standpoint of individual reactions, before introducing an Event-Reaction-Cube and describing its facets and their implications for data collection.

Throughout the paper, we illustrate the use of the conceptual model with two case

studies which span the natural and social events proposed by Polous et al. (2012).

- Brexit (an ongoing opinion formation process)
- St. Jude storm (a natural event)

In case of the Brexit, it is difficult to speak of a single event. Rather, 'Brexit' can be seen as an umbrella term for a complex and ongoing process of voter opinion formation, encompassing many individual events which will probably lead to the UK's separation from the European Union. In this context, the referendum held on June 23, 2016 represents a singular event of particular importance. The differences between event and reactions are more obvious for the St. Jude storm, a specific instance of a generic type of event, a storm, that caused major human, environmental and economic consequences while sweeping across the UK, mainland Europe and other countries on and after October 27, 2013 (Hickey 2014). These case studies portray a variety of event-reaction relationships and therefore serve as suitable candidates for demonstration of our conceptual model.

1.1 Reactions to events in location-based social media

The Oxford English Dictionary[1] defines a reaction as "something done, felt, or thought in response to a situation or event". This implies that reactions to events include not only direct actions, but also cognitive and perceptive elements. In the following, we focus on papers which have explored reactions to events as expressed in social media. A diversity of domains investigates this topic which implies that the purposes of analyses also vary widely.

[1] https://en.oxforddictionaries.com/definition/reaction

In all of the studies we analysed, a message or post published on a social media platform related to a given event is considered as a reaction. The most commonly examined social media platform, due to ease of access through the widely used API, is the microblogging service Twitter, but Facebook and the Chinese microblogging service Sina Weibo are examples of other platforms studied. Reactions may also take the form of images, for example posted to Flickr or Instagram, and text related to these, or content posted to discussion forums.

Typically, references to a given event are defined by keywords or hyperlinks contained in a message and by using a temporal window to limit data collection to the issue attention cycle around the event (Downs 1972), i.e. the period in which public attention to an event arises and drops off.

Related work on reactions to events expressed in social media can be differentiated by the category of the event the reaction is related to and by the purpose of the study. Event categories include natural disasters (Hashimoto et al. 2013), speeches (Amanatullah et al. 2013), health-related events (Szomszor et al. 2011, Fung et al. 2015, Nikfarjam et al. 2015, Meaney et al. 2016), advertising campaigns (Rodrigues 2016), criminal and terrorist events (Burnap et al. 2014, Kounadi et al. 2015; McEnery et al. 2015), protests or unrest (He et al. 2015), and entertainment-related events (Lipizzi et al. 2016). The purpose of such studies includes investigating the diffusion of reactions (Burnap et al. 2014), analysing perception of events, i.e. the attitudes and concerns triggered by an event (Hashimoto et al. 2013, He et al. 2015, Kounadi et al. 2015, Meaney et al. 2016), identifying trusted or credible information sources (Szomszor et al. 2011), event detection from reactions including monitoring (Amanatullah et al. 2013, Nikfarjam et al. 2015), assessment of the effectiveness of advertising campaigns (Rodrigues 2016),

sales prediction (Lipizzi et al. 2016) or interrelationships with news media (Castillo et al. 2014, Tsytsarau et al. 2014, Fung et al. 2015, McEnery et al. 2015). Importantly, the last topic explicitly makes the link between another medium - the influence of the press on the reactions to an event, making clear that social media reactions cannot be considered as purely a function of a given event, but rather a discourse conducted through a multitude of media around an event. This in turn points to the more general importance of context when exploring reactions. In the studies described here only He et al. (2015) and Kounadi et al. (2015) explicitly consider space in analysing reactions to events in LBSM.

1.2 Events

In contrast to research on reactions, the importance of space (and time) with respect to events is clear. In general, consensus exists in the core notion of events as *identifiers* for change. In other words, events are considered a segment of time that is "carved out of processes" (Kuhn 2012) such that they can be distinguished, referenced and memorized. This is also in accordance with the common-sense notion of events, and it can be argued that humans perceive, structure and memorize time as a sequence of discrete events of varying importance (Zacks & Tversky 2001, p. 58). In this vein, many authors argue that events function as the temporal counterpart of objects in the spatial domain and, therefore, should be treated as of similar or equal rank (Zacks & Tversky 2001, Chen 2003, Worboys 2005, Galton 2006).

The current paradigm is that both events and objects are mutually interdependent but ontologically distinct (Worboys & Hornsby 2004, Liu et al. 2008, Galton & Mizoguchi 2009). Unlike processes and objects, events do not 'persist' as a whole throughout their existence, they simply occur (Galton, 2006). Therefore, start and end are seen as core

components of events, often referred to as the *boundary* or *frame* (Zacks & Tversky 2001, Zacks et al. 2007). Each part of an event may itself consist of processes and events, arranged in a particular sequence. These sub-structures can be broken down further, which forms a unique pattern and taxonomic hierarchy (Quine 1985, Beard et al. 2008). Beard et al. (2008) propose a two dimensional event categorization between primitive and composite and expected and unexpected events. The most primitive events consist of simple physical changes which are conceived almost instantaneously. This means that, in some cases, start and end may coincide (Zacks & Tversky 2001). At other times, composite events can become so complex that they can only retrospectively be perceived as events. Frequently, these composite events will have fuzzy temporal and spatial boundaries, making computational event detection challenging (Westermann & Jain 2007) but often presenting no challenge to human observers (Zacks et al. 2007). This uncertainty is an important characteristic for the everyday-connotation of events, and is expressed in the second distinction from Beard et al. (2008), expected versus unexpected. Expecting an event or becoming aware of it while it is happening requires knowledge (Zacks & Tversky 2001). Sometimes, it is easy to spot events because their temporal sequence is very familiar to us. At other times, events are unexpected because we have not experienced them before (Bell 2012). In other words, some people may perceive an event while it passes unnoticed for others (Worboys 2005). This intangible nature of events poses difficulties for research dealing with reactions to events, because events require both a physical manifestation and an explicit 'cognitive labelling' (Claramunt & Jiang 2000). A further challenge is seen in the granularity of events. Zacks & Tversky (2001) argue that humans possess a pre-conditioned range of scales where they are particular sensitive to events. Finally, Polous et al. (2013) categorize events in three basic types, natural, social and artificial. Linking these concepts, events

can occupy a continuum of granularity scales and types from the micro-level (e.g. artificial events such as computer clicks) to human-scale events (e.g. the social/human-centered view, e.g. someone's vacation) to the macro-scale (e.g. astronomers consider a merger of two galaxies, spanning millions of years, as an event).

1.3 Characterising events and reactions

I keep six honest serving-men
(They taught me all I knew);
Their names are What and Where and When
And How and Why and Who.

Rudyard Kipling, Just So Stories, 1902

Key to any framework seeking to analyse reactions to events is a definition of the dimensions through which both reactions and events can be described. As pointed out by Teitler et al. (2008), these dimensions form the core of a description of an event, and include not only ways of describing (What, Who, Where, When) but also explaining (How and Why). Answering these questions can be seen as a way of characterising the context of an event, and when we explore LBSM (or indeed news stories), the reaction to such an event. Thus, Robertson & Horrocks (2017) state that "context can be defined as any information that can be used to characterize or improve interpretation of an entity". In practice, as is shown in Table 1, despite a plethora of definitions of context, these are often Kipling's When, What, Where and Who. Interestingly, How and Why, which might be considered the goal of the analysis of reactions to an event are typically not considered, or subsumed into the thematic facet.

	Etzion & Niblett (2010)	Shatford (1986)	Zimmermann et al. (2007)	Dustdar & Rosenberg (2007)
Temporal Facet	Temporal context	When?	Time	Time
Spatial Facet	Spatial context	Where?	Situation	Location
Social Facet	Segmentation-oriented context	Who?	Role	Identity
Thematic Facet	State-oriented context	What?	Interest topic	Activity/ Status

Table 1: Different context definitions in literature assigned to the 4 facets of the conceptual model proposed herein.

The closest analogy with regard to event-reaction-research comes from Etzion & Niblett (2010), who define context as factors that influence how an 'event processing agent' (p. 148) might act under certain *situations*. The authors categorise these situational factors in four 'context dimensions'. Etzion & Niblett (2010) state that "Context plays the same role in event processing that it plays in real life. A particular event can be processed differently depending on the context in which it occurs, and it may be ignored entirely in some contexts" (see the above, p. 144), but the authors also stress that "In the user domain consideration of what should trigger a reaction depends on the user's perspective; this is rather different from the computer domain […]" (*ibid*, p. 297).

2 Conceptual model

2.1 Individual reactions, events, and their context

We introduce a conceptual model which aims to incorporate key notions introduced in our literature review, in particular clearly separating reactions and events, and allowing a range of scales and granularities. The aim of our conceptual model is to provide a framework suitable for use in the analysis of reactions, and we discuss its practical implications in §3 before illustrating the use of the framework in analysis in §4 for one of our case study examples.

In LBSM individual reactions (e.g. a single tweet in response to some salient event) can potentially be shared (e.g. re-tweeted) among millions of users, and thus change the nature of the original event reported. It follows that, unlike top-down approaches conventionally applied when characterising events, investigation and characterization of collective reactions on LBSM requires a bottom-up approach, based on the aggregation of knowledge starting from such individual reactions (c.f. Brabham 2013). Consequently, individual reactions over time, in the form of the creation and sharing of content online, are base entities and their definition is the first element of our conceptual model.

An *individual reaction* is a single reaction from one actor to one event that cannot be further differentiated in a meaningful way. We characterise an individual reaction as a tuple $r = (e, p^r, t^r, s^r, a^r)$, consisting of identifier to a referent event and four facets describing the reaction:

- e is the event that motivated the reaction;
- p^r is the actor who reacted (the *social facet*);
- t^r is the time of the reaction (the *temporal facet*);
- s^r is the spatial location of the reaction (the *spatial facet*);
- a^r is a combination of thematic attributes characterizing the reaction (the *thematic facet*; i.e. how specifically did the person react?)

In our conceptual model, p^r is an actor who perceives an event e or information about it and reacts. Typically, this will be an individual person, however in LBSM it is often challenging to determine whether a social media profile represents fictitious or real persons, bots or even 'cyborgs' (You et al. 2012). Therefore, p^r may also be considered

as an ‘avatar’ representing an organization or a group of individuals.

We emphasise that (1) all LBSM posts are reactions, (2) all reactions have a referent event and (3) all facets are present in the characteristics of a reaction. However, all facets (4) need not to be regarded of equal relevance for a particular analysis just as they (5) need not to be available in all LBSM datasets. It follows that, in LBSM research exploring reactions, both reactions and events are core components in the analysis process. Importantly, while reactions are not independent of the referent event, an event itself can be considered independently.

Therefore, we define an *event* as a tuple $e = (t^e, s^e, P^e, a^e)$, where

- t^e is the time when the event happened (an instance or interval in time);
- s^e is the spatial location associated with the event. It may be modelled as a point, or a continuous area or path, or a set of disjoint points, areas or paths;
- P^e is the set of people involved in the event, which may be empty;
- a^e is a combination of thematic attributes characterizing the event.

Based on the notion of events introduced by Beard et al. (2008), we distinguish between simple events *e* and complex events *E*. Simple events are the smallest observed entities that people perceive and react to (e.g. a tweet that is observable, a single rumble of thunder etc.). We then consider complex events as collections of events arranged in a particular pattern. These complex events are the typical subjects of our analysis and the case studies in this paper. For example, the announcement of the results of the Brexit Referendum or damage to an individual house by St Jude’s Storm can be considered as simple events, while the build up to and aftermath of the referendum, or the passage of the storm across France would be treated as complex events.

2.2 Event-Reaction-Hypercube

Based on the definitions introduced above, it becomes obvious that events and reactions are difficult to separate. Although it is possible to study the physical appearance of events entirely through objective measurements (e.g. measuring wind speeds in the case of St. Jude storm), an event's overall meaning and importance cannot be understood if separated from individual interpretations and perceptions in the form of reactions. Conversely, without identifying the referent event(s) for reactions, underlying motivational factors that affect behaviour, including causalities in the formation of collective reactions, remain hidden. Therefore, we consider events and reactions as occurring in a single system, which we refer to in the following as the Event-Reaction-Hypercube (or simply ER-Cube). The ER-Cube has two poles: the physical environment (as sensed) and the experiencing person (who perceives, attributes meaning, feels, remembers, judges etc.). These poles refer to the facet dimensions of events and reactions respectively. In literature, the people-pole is also sometimes referred to as the *experiential* aspect of events (Lyons 1977, Westermann & Jain 2007, Galton 2008), to emphasize the subjective experience of events and the personal meanings attached to them.

By considering and distinguishing both poles, the ER-Cube helps an analyst distinguish between two perspectives. In the first, events are the core subject of analysis and reactions are only consulted for supplementing missing information. This is the case, for example, in event detection, such as shown by Andrienko (2015), where it is possible to infer the occurrence of events from user reactions. In the second, where the focus are reactions, the goal of analysis is to understand individual people's behaviour and motivation, and events are either considered incidental or provide the general frame of analysis that is given from the outset. An aid to distinguish between these two sets of

information is provided in Table 2, where the facets of the Event-Reaction-Cube are identified and described with respect to individual reactions and referent events.

	Individual Reaction	Referent Event (query space)
Temporal Facet	includes the history of the previous reactions of this individual and, more generally, the previous individual history consisting of all kinds of events this individual reacted to	includes (1) characteristics of the time when the event happened; (2) history of happenings preceding the event; (3) expected events in the future. Characteristics of the time include event position with respect to temporal cycles (daily, weekly, seasonal), whether it is a holiday or school vacation period, etc.
Spatial Facet	includes characteristics of the location of the actor, i.e. the area or place of the reaction; and, more generally, the previous individual history consisting of all kinds of spatial reaction footprints this individual left behind	includes (1) geographic characteristics of the territory where the event happened, such as land cover and land use; (2) socio-demographic and economic characteristics of this territory; (3) various kinds of spatial objects located in the event neighbourhood
Social Facet	includes information on the identity of the actor such as demographic and cultural connections and the society the individual belongs to; this encompasses personal opinions, beliefs, attitudes, values, norms, and preferences etc.	when an event involves or affects a group of people, social context includes the structure of the society this group belong to and relationships within the society
Thematic Facet	includes any additional attributes that characterize or accompany a reaction of an individual such as emotions, situational attention or thematic interest	includes any additional descriptive elements of the event such as physical measurements (temperature, wind speed), or range and type of affected thematic topics

Table 2: The 4 facets of reactions and events. All facets are present in a reaction, while only time is required to define a referent event (cells with grey background are optional facets).

The initial consideration of the referent event within which reactions are analysed is defined as a *query space,* the maximum dimensional extent of facets considered relevant by an analyst. The resulting hypercube represents different idealized relationships between reactions and to a common referent event as expressed in similarity measures. Each facet may be represented in multiple dimensions, e.g.

- Temporal Facet: temporal offset to the referent event in terms of minutes, days or weeks etc. (e.g. see temporal ordering relations for intervals and moments, Allen & Hayes, 1989).
- Spatial Facet: distance or topological relationship with the referent event (e.g. see topological spatial relations from Egenhofer & Franzosa, 1991)
- Social Facet: cultural similarity measure in the form of demographic make-up of the individuals reacting (e.g. age, gender, social group etc.)
- Thematic Facet: similarity measure for thematic interest or sentiments in regard to the referent event (e.g. mood, stance, focus or attention of the actor as accompanying the reaction)

These measures of similarity link individual reactions and relate directly to *agency*, a concept that denotes people's involvement in an event. For example, for some natural events, such as St. Jude storm, people may be active observers experiencing the storm or passive observers viewing media reporting on the storm, but the passage of the storm itself is not influenced by these individuals. The Brexit referendum, on the other hand, is a purely social process. A specific group of people, UK citizens, directly participated in this event, and had at least some agency in the referendum's outcome. Another group, the population of the European Union, had limited to no agency in the referendum, but is, to some degree, affected by its outcome. Other groups outside Europe were neither involved nor perhaps directly affected by the referendum and its consequences. This means that the degree of agency is a continuum, representing nuances of people's (perceived) ability to change or react to an event (c.f. Davidson 1980). Therefore, depending on the respective circumstances coinciding with a specific situation, such as a person's spatial location at a specific time, the social groups this person feels affiliated with (social facet), or the current mood (thematic facet), there exist varied degrees of

agency with respect to reactions in response to events. Consequently, individual reactions can be grouped and aggregated into different sets of collective reactions based on similarity measures across facets. This enables analysts to understand and study typical and recurring patterns of behaviour, and start to explore the how and why of reactions.

Similar to the 'context partitioning' proposed by Etzion & Niblett (2010) for artificial event processing agents, we refer to the process of grouping individual reactions into sets of collective reactions (§2.3), based on similarity measures, as *facet partitioning*. This process depends on two separate steps:

- the definition of the referent event for selecting the initial set of reactions to be considered (§2.3.1) and
- partitioning of individual reactions into groups based on similarity measures (§2.3.2 to 2.3.5).

2.3 Collective reactions

A *collective reaction* is a set of individual reactions to the same referent event, i.e., a set of tuples $R(E) = \{r_i = (E, p^{r_i}, t^{r_i}, s^{r_i}, a^{r_i}) \mid 1 \leq i \leq N\}$ with a common E. For a given collective reaction $R(E)$ let $P(R(E)) = \{p^{r_i} \mid 1 \leq i \leq N\}$, $T(R(E)) = \{t^{r_i} \mid 1 \leq i \leq N\}$, $S(R(E)) = \{s^{r_i} \mid 1 \leq i \leq N\}$, and $A(R(E)) = \{a^{r_i} \mid 1 \leq i \leq N\}$. Here, $P(R(E))$ is the set of people who reacted to the event E, $T(R(E))$ is the set of time moments when the reactions happened, $S(R(E))$ is the set of spatial locations where the reactions occurred, and $A(R(E))$ is the set of ways of reacting, i.e., all combinations of values of the thematic attributes that occurred in $R(E)$.

2.3.1 Referent event

A referent event, typically defined by an analyst, forms the basis for selecting the initial set of reactions to be considered in analysis. Events may cover a range of granularities crossing different hierarchical levels. For instance, in the case of St. Jude Storm, the subject of analysis can be seen as both a unique event, as an instance of a more general, universal class, such as "cyclones", "UK storms", or "extreme weather events" etc., or a collection of sub-events. From the outset, all storm events are characterized by a base of common attributes, allowing them to be collectively referenced and recognised as such. The global class of events can be grouped in many different sub-classes and sub-events. Attributes may vary across different storms (e.g. blizzards, cyclones and hurricanes) or across sub-events of the same storm (e.g. wind damage to trees), or a particular instance or token (Galton 2015) such as a single fallen tree that caused specific consequences. In all of these cases, a referent event could be characterized by different attributes. This means that an analyst studying collective reactions may, depending on the question being investigated, treat similar, recurring events as a single subject for analysis (e.g. a set of events E), or divide events into many sub-classes (E_1, E_2, E_3 etc.) (c.f. Allen et al. 1995).

Associating reactions to a chosen referent event is a key aspect in LBSN analysis and can be regarded a sub-problem of causality modelling (Tsytsarau et al. 2014). Depending on the definition of the referent event, the association process may be straightforward. For example, in case of the *Brexit*, a single term emerged from the discourse which consequently helps researchers to associate collective reactions. In most contexts, however, such direct identifiers may not exist and association may introduce uncertainty. In these cases, verifying associations between reactions and referent event is a non-deterministic process. How much effort, discretion, and scrutiny

an analyst is willing to invest largely depends on data availability, analysed context and desired accuracy of results. An example approach to association and validation is given in §4 for reactions to St Jude storm, which illustrates how analysts can use a wider set of search terms and multiple facets to select and verify reactions.

2.3.2 Spatial and temporal facet: where and when?

In the context of reactions and events time and space are intertwined, and thus they are discussed together here. An important characteristic is that at a particular place and time, only one observer can be physically present. Therefore, two reactions, even from the same person, are considered distinct. Similarity may refer to the temporal and spatial proximity of reactions to a common referent event. In other words, two reactions from nearby places and times might be expected to have a higher degree of similarity with regard to a particular event. Reaction-event relationships can be grouped spatially by notionally meaningful regions (e.g. the same country, region, city or neighbourhood, and at the same temporal offset in minutes, hours, days or weeks, respectively). At the same time, a wide range of spatial and temporal clustering methods allow aggregations based on the nature of reactions themselves and their spatio-temporal properties (e.g. Beard et al. 2008, Andrienko et al. 2015). The following illustrate some potential ways of grouping reactions in typical space-time relations using our model:

- Contain, equal and unequal (Egenhofer & Franzosa, 1991):
    - in the case of St. Jude storm, $s^{r_i} \in s^e$ may refer to reactions from persons who were directly affected by the storm or at least were direct observers, whereas $s^{r_i} \notin s^e$ may include reactions as expressions of sympathy or surprise.

- reactions with a spatial location outside that of the storm's impact area s^e or outside its impact timespan t^e may also come from people directly affected. For instance, this would be the case if someone was a direct witness on their vacation, but only after returning home (e.g. to some not affected region) decided to report on the incident on social media.

- Before, after (Allen & Hayes, 1989):
  - a reaction preceding its referent event ($t^{r_i} < t^e$) means that an event is expected or anticipated, e.g. someone might post after booking a flight (the reaction) to escape a forecasted path and peak of a storm (the referent event)
  - reactions subsequent to a referent event ($t^{r_i} > t^e$) always come in response, and may include an actor's personal evaluation of the event *as it happened* if this person was a direct witness or observer, e.g. someone sharing a picture of an accident as a consequence of St. Jude storm

Implications for data collection, representation, and analysis

Because different sets of spatial and temporal information may be available, the analyst must take care in choosing and selecting the right kind of data for representing relationships. Firstly, as Nov et al. (2009) point out, reactions on LBSM consist of at least two steps, content-creation (1) and content-contribution (2). Not all creation of content is instantly followed by the contribution process (e.g. taking of a picture followed by uploading to a social media platform). Secondly, the availability of spatial and temporal information varies rather widely across current LBSM. For instance, while Flickr offers both the putative time of content-creation step (i.e. the photograph's timestamp) and the time of content-contribution (i.e. the upload time), only the nominal

location of content-creation is available from geotagged photographs. By contrast, Instagram only offers the location of the content-sharing step of the reaction (Chen et al. 2017). Conversely, on Twitter only the location of content-contribution is available, and only if the user opted-in to this feature. Notwithstanding these options, a researcher may still infer the spatial or temporal relationship of reactions to a referent event based on other available information such as textual references (Hahmann et al. 2014) or a user's 'home location' (Hecht et al. 2011). Therefore, which data is finally used to represent the spatial and temporal relationship of reactions to referent events depends on both, suitability and availability of data.

2.3.3 Social facet: who?

The social facet describes an actor's identity, encompassing their wider affiliation with social groups or cultures. The underlying assumption is that referent events involve or affect different groups of people differently. In other words, whether someone feels affected or unaffected by an event, is considered a participant, observer or witness or takes a positive or negative stance towards an event depends, to some degree, on the social background of this individual. This may encompass complex aspects including political orientation, beliefs, values, norms and preferences, which express a continuum of people's relationships towards an event that (often unconsciously) affect reactions. Because of the complexity involved, these social relationships between reactions and events are not typically directly found in LBSM data, but can be explored based on partitioning including:

- an actor's origin (e.g. USA, Canada or Australia),
- language,
- gender,

- age,
- occupation or
- differentiation between local population and visitors/tourists (in respect to the event footprint).

Implications for data collection, representation, and analysis

The social facet is perhaps most difficult to infer from available data on current LBSM, and at the same time, portrays the most sensitive set of privacy-relevant information because it can be misused for disputed practices of 'social profiling' (Mitrou et al. 2014). This is also because, depending on the energy an analyst is willing to invest, most data attributes in LBSM contain information on user identity. This ranges from directly available information (that the user explicitly chooses to share), such as 'home location', as an indicator for origin or ethnicity, or the current language setting, to more detailed information that becomes available when taking into account a wider set of information and methods of pattern detection. For instance, Saito et al. (2015) classified users into different groups, such as 'Businesspeople', 'Frequent Bloggers', 'IT People', or 'English Speaking', based on their long-term posting behaviour.

2.3.4 Thematic facet: what?

The difference between the thematic and social facet is in the relation to the actor. Thematic attributes include immediate situational aspects that affect reactions from an actor in a particular situation (e.g. sentiments, feelings, emotions, but also co-occurring aspects in the surrounding of an actor or any other attributes of the reaction environment). Therefore, unlike social attributes, thematic attributes change frequently from one reaction to another. Possible partitions include but are not limited to emotional states of the actor (e.g. positive, neutral, negative), as inferred from emoticons or based

on sentiment analysis (Hauthal 2013), or the stance of different actors to events as inferred from semantics such as titles, comments or descriptions etc. (Zeng et al. 2016). Keywords such as hashtags, for example, may indicate what aspects of an event were perceived as being of particular importance (Towne et al. 2016), or refer to individual event consequences or actions people have undertaken or plan to undertake (Gao et al. 2014).

Implications for data collection, representation, and analysis

Specific attributes that are attached to LBSM reactions by actors, such as tags (Flickr) or hashtags (Instagram, Twitter) can be used for partitioning based on the selection of one specific term or the co-occurrence of multiple terms. In this regard, an analyst will frequently need to compromise between increasing thematic accuracy, based on filtering techniques, and a reduced significance and validity of data due to sampling effects (Choudhury et al. 2010). Furthermore, language is not static and new terms can emerge at any time from the public discourse to portray specific meaning of reactions to events. For example, for some ‘Brexit’ supporters, the referendum outcome meant a complete reverse of sentiment, which was later coined the 'Bregret' movement (Dearden 2016), a portmanteau of "Brexit" and "regret". In the context of user attitudes towards such controversial topics, for instance, Gao et al. (2014) inferred user opinions and attitudes based on retweeting distribution.

2.3.5 *Information spread*

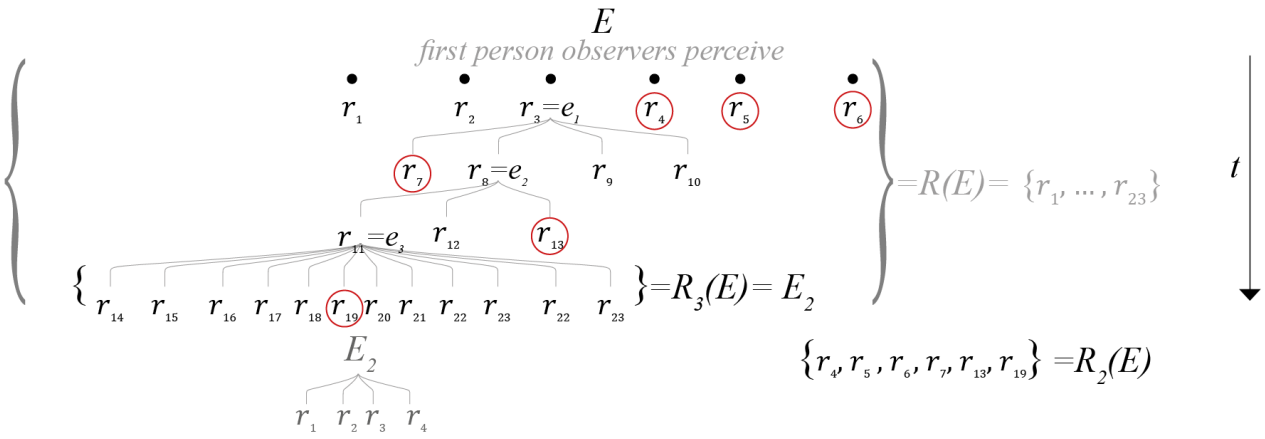

Figure 1: Illustration of a referent event E and all collective reactions $R(E)$ with two example partitions R_2 and R_3. During the information spread that occurs in response to E, a new referent event E_2 is formed by partition R_3.

A specific situation arises when reactions become the referent event for other reactions, an important characteristic of the information spread that occurs in LBSM (Fig. 1). For purposes of formalization, let $l(r_i, r_k)$ represent a directed link between individual reactions r_i and r_k such that r_i appeared in response to r_k. A case when r_i appeared in response to multiple reactions $\{r_k, r_m, \dots\}$ can be represented by a set of binary links $\{l(r_i, r_k), l(r_i, r_m), \dots\}$. We use the notation $L(R(E))$ to denote the set of all known links between individual reactions within $R(E)$. The event information spread in response to a common E forms a unique structure and hierarchy, which can be conceived as an additional facet of $R(E)$. In the context of information spread, similarity refers to the position of the reaction in the hierarchy (e.g. 1st, 2nd or 3rd –'generation viewers', c.f. Crane & Sornette 2008). In Figure 1, three possible partitions of collective reactions are illustrated,

(1) $R(E)$ representing the sum of all reactions to E,

(2) $R_2(E)$ as a specific subset of individual reactions that are grouped based on a common composition of facets (following §3.3.1 to 3.3.4), and

(3) $R_3(E)$ representing a partition of collective reactions that is formed based on similar position in the information spread hierarchy.

Implications for data collection, representation, and analysis

Direct links between reactions are available from some LBSM in the form of unique identifiers (e.g. linking a comment to the referent photo on Flickr, or a retweet to the referent tweet.). However, various other approaches exist to partitioning collective reactions based on the spread of information. For example, Tsytsarau et al. (2014) model user behaviour in response to events as a convolution between an event's importance and a 'media response function' and, based on this, categorize four types of event-reaction relationships, expected impacting, expected non-impacting, unexpected impacting, and unexpected non-impacting (or transient). By contrast, Crane & Sornette (2008) classify collective reactions into four characteristic classes of collective human dynamics ('endogenous-subcritical', 'endogenous-critical', 'exogenous-subcritical' and 'exogenous-critical'), based on the spread of information. An important distinction must be made between reactions that directly relate to the referent event (e.g. from participants, witnesses or direct observers, as is illustrated with the first row in Fig. 1) and other reactions which are influenced or triggered at later times ($r = e$). This is particularly important when studying LBSM since first-hand accounts are often stripped of relevant information, or supplemented based on personal motives and goals (He et al. 2015). These effects may provoke reactions that are not directly related to the original referent event. Any collective reaction may therefore be classified as a new referent event (see example in Fig. 1, $R_2 = E_2$). This means that relatedness can be seen as a continuum of event-reaction ties ranging from strong through weak to non-existent.

3 Analysis tasks and workflow

Having set out a conceptual model explicitly linking reactions and events, an important question how can we use this model in analysis? In non-trivial analysis, the analyst strives to understand the characteristics of the studied phenomenon *in relation to the context*. Here, there are two high-level subtasks: (1) characterize the phenomenon and (2) relate the characteristics to the context. In our case, the phenomenon is a collective reaction. Its characteristics need to be derived from the characteristics of the individual reactions. These refer to the facets of the collective reaction and can include, for example, similarity measures of distribution, variance or dynamics in meaning and selective attention. After these overall (collective) characteristics are derived from elementary data, the analyst studies their relationships to the respective components of the context. Recall that the context for reactions includes the characteristics of the referent events (§2.1). While the general order of workflow is not fixed, the following key steps can be summarized:

- Define the referent event or set of events that is of interest
- Define analysis tasks
    - Define task-relevant facets and relationships
- Select relevant reactions
    - Choose suitable data source(s)
    - Identify reactions to the chosen referent events among all reactions
    - Enrich, i.e., generate task-relevant attributes (e.g. topics, sentiments)
- Choose visualization and analysis methods depending on tasks and task-relevant facets and relationships. e.g.,
    - Spatial facet, spatial relationships: maps, spatial aggregation, spatial clustering, spatial analysis methods;

    - Temporal facet: temporal aggregation, time graph, time series analysis; space and time: spatio-temporal clustering, space-time cube
    - Thematic and social facet: tag clouds, tag maps, graphs, networks.
- Validate and interpret results by taking into account additional information from outside LBSM (normalization, validation, impact):
    - Not all reactions are available from LBSM (sampling bias)
    - Some reactions may be more prominently represented in LBSM data (representativeness)
    - Interfaces influence user reactions and may therefore distort results (suitability)

The types of analysis tasks for studying collective reactions are summarized in Table 3. The rows and columns correspond to the information facets. The cells along the diagonal include the tasks focusing on a single facet. The remaining cells include the tasks on studying pairwise relationships between the facets, i.e., how elements of one facet are distributed or vary with respect to the other facet. The latter can be metaphorically seen as a "base" and the former as an "overlay" spread over this base. The relationships between two facets can be viewed from two perspectives depending on which of the facets is chosen as the base for the other. In Table 3, the columns correspond to the facets treated as the bases and the rows correspond to the facets whose distribution or variation with respect to the base facet is studied.

	Spatial (A)	**Temporal (B)**	**Social (C)**	**Thematic (D)**	**Information spread (E)**
Spatial (1)	Properties of ***spatial distribution*** of reactions, e.g., scattered, concentrated, clustered, ... Relationships to spatial context.	Evolution of the spatial distribution properties over time. Relationships of the changes to the temporal context.	Differences between spatial distribution properties of reactions from different population groups. Relationships of the differences to the social context.	Differences between spatial distribution properties of different kinds of reactions. Relationships of the differences to the thematic context.	Dependence of the spatial distribution on the information spread characteristics.
Temporal (2)	Variation of the reaction development characteristics across space. Relationships of the differences to the spatial context.	***Reaction development*** over time: emergence, increase, peak(s), decline, … Relationships to temporal context.	Variation of the reaction development across reacting population groups. Relationships of the differences to the social context.	Differences between development properties of different kinds of reactions. Relationships of the differences to the thematic context.	Dependence of the temporal development on the information spread characteristics.
Social (3)	Variation of the social characteristics of reacting population groups across space. Relationships of the differences to the spatial context.	Variation of the social characteristics of reacting population groups over time. Relationships of the changes to the temporal context.	Socio-demographic characteristics of reacting ***population groups***. Relationships to the social context.	Socio-demographic differences between population groups reacting in different ways. Relationships of the differences to the thematic context.	Dependence of the reacting population groups on the information spread characteristics.
Thematic (4)	Variation of the reaction characteristics across space. Relationships of the differences to the spatial context.	Evolution of the reaction characteristics over time. Relationships of the changes to the temporal context.	Variation of the reaction characteristics over population groups. Relationships of the differences to the social context.	***Reaction characteristics***: attitudes, emotions, … Relationships to the thematic context.	Dependence of the reaction characteristics on the information spread.

Information spread (5)	Information spread over space. Relationships to the spatial context.	Information spread over time. Relationships to the temporal context.	Information spread over social groups. Relationships to the social context.	Differences between spreading of different kinds of reactions. Relationships of the differences to the thematic context.	***Information spread characteristics*** Relationships to information context

Table 3: Task matrix for studying collective reactions based on the proposed framework.

4 Using the conceptual model to explore reactions to St Jude's Storm

In the following we set out to briefly illustrate the use of the proposed conceptual model through applying it to one of our case studies. Our aim here is not, *per se*, to analyse the reactions to this event in detail, but rather to illustrate how the conceptual model developed (§2), in conjunction with the resulting analysis workflow (§3) can improve our ability to understand collective reactions in LBSM.

We analysed the St. Jude storm, and chose to do so using user contributed photo data from Flickr. As set out above, the analysis process is characterized by two distinct steps, (1) identification of relevant reactions and (2) characterization of reactions to understand user behaviour. The initial selection of contemporaneous reactions (1) poses difficulties because the storm was given many names, and these references were only used after the event. Furthermore, many reactions may have been indirectly motivated by effects of the storm with people not being consciously aware of it while reacting (taking and tagging photographs). A possible approach is to define a relatively wide initial query space for each facet. For querying the thematic facet, for example, it is possible to use a set of search terms that indirectly relate to the general class of storm events (including translated terms in Dutch, German and French).

The original general structure of LBSM posts (before extraction of task-relevant thematic attributes) can be represented as a tuple $m_i = (W_i, s_i, t_i)$, where W_i is a text (e.g., a message or a title of a photo, possibly, joined with tags when available) consisting of words, s_i is the spatial location, and t_i is the time of the *i*-th post in a set of social media posts $M = \{m_i | \ 1 \leq i \leq N^M\}$. Note that the text W_i belongs to the thematic facet of a reaction, i.e., it is one of the attributes a_i appearing in the definition of a reaction. W_i is a primary attribute existing in the original LBSM data; further thematic attributes can be derived from it during the process of data analysis.

Let W^{storm} be a set of storm-related terms, or keywords:

$$W^{storm} = \{storm, cyclone, gale, gust, hurricane, blow, wind, windy\}$$

A query using these keywords can extract a subset of posts supposedly referring to storms:

$$M^{storm} = \{m_k \in M | \ W_k \cap W^{storm} \neq \emptyset\}$$

However, not all posts in M^{storm} may be related to the St Jude storm. To approximate $R(E)$, where E = St Jude storm, more closely, the query needs to be refined by taking into account the temporal and spatial references of the posts. Based on the known information about the event we define a time window $T\big(R(E)\big) = [t_0, t_1]$ with $t_0 = 26/10/2013$ and $t_1 = 29/10/2013$. This time interval includes the time when the storm was happening but is wider than that, to be able to include reactions that anticipated the storm based on weather forecasts as well as reactions posted after the storm. It is also reasonable to limit the spatial extent of analysis to $S\big(R(E)\big) = \{s_i | \ s_i \subseteq s^E\}$, where

$s^E = \{Ireland, UK, France, Belgium, Netherlands, Denmark, Sweden, Germany\}$,

based on the known impact footprint of St Jude storm. Hence, the complete query for extracting the LBSM data subset M^E that approximates $R(E)$ can be represented as follows:

$$M^E = \{m_k \in M | \, W_k \cap W^{storm} \neq \emptyset \wedge t_k \in T\big(R(E)\big) \wedge s_k \in S\big(R(E)\big)\}$$

With the use of these query constraints, Flickr returns a total number of 2100 potentially relevant reactions from 645 users. However, this set of reactions M^E may still include false positives ($m_j \in M^E \wedge m_j \notin R(E)$), i.e., reactions that do not refer to the St Jude storm, whereas some reactions that do refer to it may be missed ($m_j \in M \wedge m_j \in R(E) \wedge m_j \notin M^E$), e.g., due to use of different terms, or misspelling of a term, or being posted beyond the specified time window. In other words, it is not clear whether the chosen thematic query is suitable to associate reactions with St Jude Storm (see §2.3.1). Validity in this context refers to the appropriateness of the selected set of terms, which can be verified by comparing expected to observed behaviour across other facets. The hypothesis (i.e. the expected behaviour) is that storm-related reactions on Flickr should increase only during storm events and in areas close to storms. This task is described by D1 and D2 in the matrix (Tab. 3, §3).

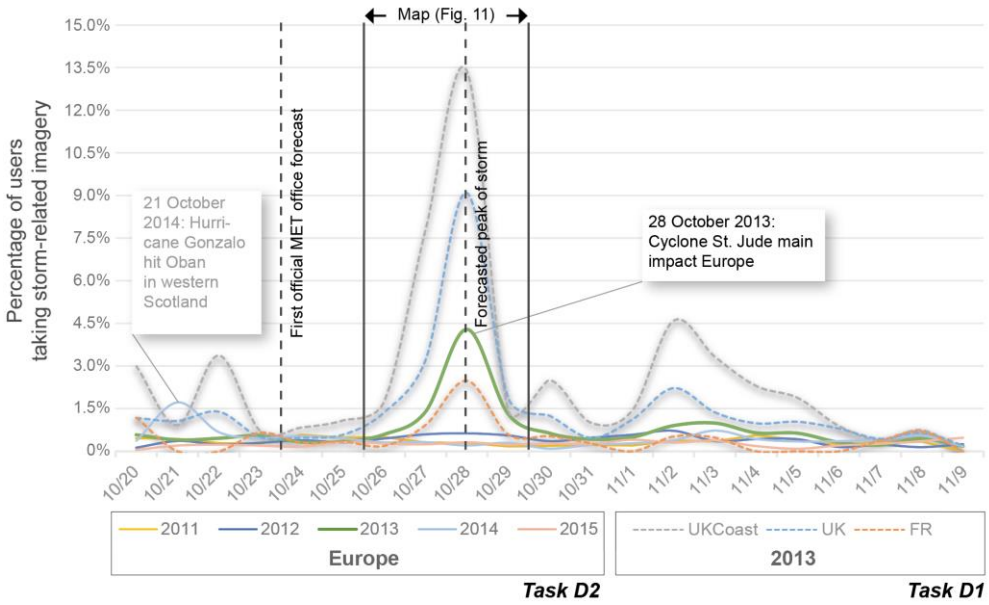

Figure 2: Percentage of active Flickr users who took storm-related photos (M^{storm}) for different partitions in space and time.

In Figure 2, additional data is taken into account to validate M^{storm}. Relative reaction amplitude (i.e. observed behaviour) is compared for five equal periods in 2011 to 2015 (task D2) and, for the year 2013, across four areas Europe, France, UK and the 10 kilometre coastal zone of UK (task D1). Within the three day period of St Jude's main impact in 2013 a total number of 137,500 photos was taken and uploaded to Flickr for Europe, with a peak of more than 4% of all Flickr users taking storm-related pictures on October 28. Only one other peak, with a significantly lower amplitude of contribution, is visible for the time from October 20 to 22 in 2014, when Hurricane Gonzalo hit Oban in western Scotland. No other storm during the same period in 2011 to 2015 provoked a similar reactions amplitude on Flickr, which can be seen as both a corroboration of suitability of chosen query space (M^E) and an indicator of the severity of St Jude's impact. The largest percentage of Flickr users reacted in coastal areas of southern England and along sections of the mainland coasts near the English Channel and Strait of Dover (10 to 25% of all Flickr users contributed storm-related pictures in 2013 from these areas). These observations further corroborate what could be expected based on the time and recorded path of the storm, and therefore represent a possible validation of our initial selection of relevant reactions.

For our study case, we now confirmed a reasonable suitability of our selection criteria, but know little about the actual characteristics of these 2100 selected reactions. Since we are interested in how groups of users reacted to the storm, we focused on the thematic facet using user tags as a starting point. Our aim was to reduce the dimensionality based on the thematic facet such that we could identify different

collective reactions $R_{1\ldots n}(E)$ to the St. Jude storm, and relate these back to space (and potentially time) for interpretation. Our basic workflow was as follows[2]:

1. We group tags according to users to create individual documents, filtering terms used by less than four users – this results in a total of 545 documents associated with 435 unique terms. Grouping tags according to potential users may allow us to better understand reactions in terms of demographics, since we use individuals for grouping (Task D3).
2. To further reduce dimensionality we clustered documents using Latent Dirichlet Allocation (Towne et al. 2016) outputting 10 topics. By doing so we aim to create an interpretable number of collective reactions (Task D4) (Figure 3).
3. We used the tool LDAvis (Sievert & Shirley 2014) to allow us to interactively explore the terms associated with collective reactions and to visualise topic similarity (Task D4) (Figure 4).
4. We interpret the resulting collective reactions and associated terms and project these back into space (Task D1) (Figure 5).

[2] A Juypter notebook showing the complete process is available in the supplementary materials for this article

Topic 1: storm wind nederland netherlands beach stormy holland weer paris amsterdam (279/87/98%)
Topic 2: beautiful autumn nature outdoors love day weather skyautumn happy cool (21/14/75%)
Topic 3: clouds storm sky rain weather water night river city dark (143/71/47%)
Topic 4: france white tempête black windy lake mer ciel automne monochrome (81/33/100%)
Topic 5: clouds weather sun sky cloud cloudy sunset green rainbow rain (112/53/84%)
Topic 6: autumn autumnstorm october weather fall nature leaves tree skyautumn storm (142/53/97%)
Topic 7: sea storm waves beach coast wind stormy wave water weather (463/118/95%)
Topic 8: clouds sunset germany wolken sturm herbst storm sky deutschland wetter (174/40/100%)
Topic 9: storm tree trees damage road street wind path nature old (411/40/99%)
Topic 10: england storm uk london october stjude unitedkingdom jude west ukstorm (99/36/100%)

Figure 3: Ten topics produced by LDA and corresponding ten most probable terms, denoting different sets of collective reactions $R_{1\ldots10}(E)$. Bold topics are projected back to space in Figure 5. In parentheses: Number of Photos / Number of Users / Percentage of Photos taken Local to User Home Country

Figure 3 combines several key pieces of information. Firstly, the terms which contribute most to document membership are illustrated. A number of initial interpretations can be made. The appearance of the seed terms used in extracting storm related data (e.g. storm, sturm, tempête) demonstrates that these terms are not used equally by all users, and thus can still contribute to the allocation of a user to a particular cluster. Secondly, the contribution of language to generating clusters (e.g. $R_1(E)$, $R_4(E)$, $R_8(E)$) and the related use of associated toponyms demonstrates a broad link back to space. Thirdly, and in terms of thematic reactions most interestingly, we observe some distinct classes of reactions. For example, reactions in $R_7(E)$ seem to correlate to coastal locations, $R_8(E)$ to weather related terms in Germany and $R_9(E)$ to storm damage. By exploring the semantic similarities between collective reactions (Figure 4) we note that the damage topic partition appears to have many similarities with partition $R_{10}(E)$, whose most prominent terms are toponyms and other proper nouns referring to the UK and the storm.

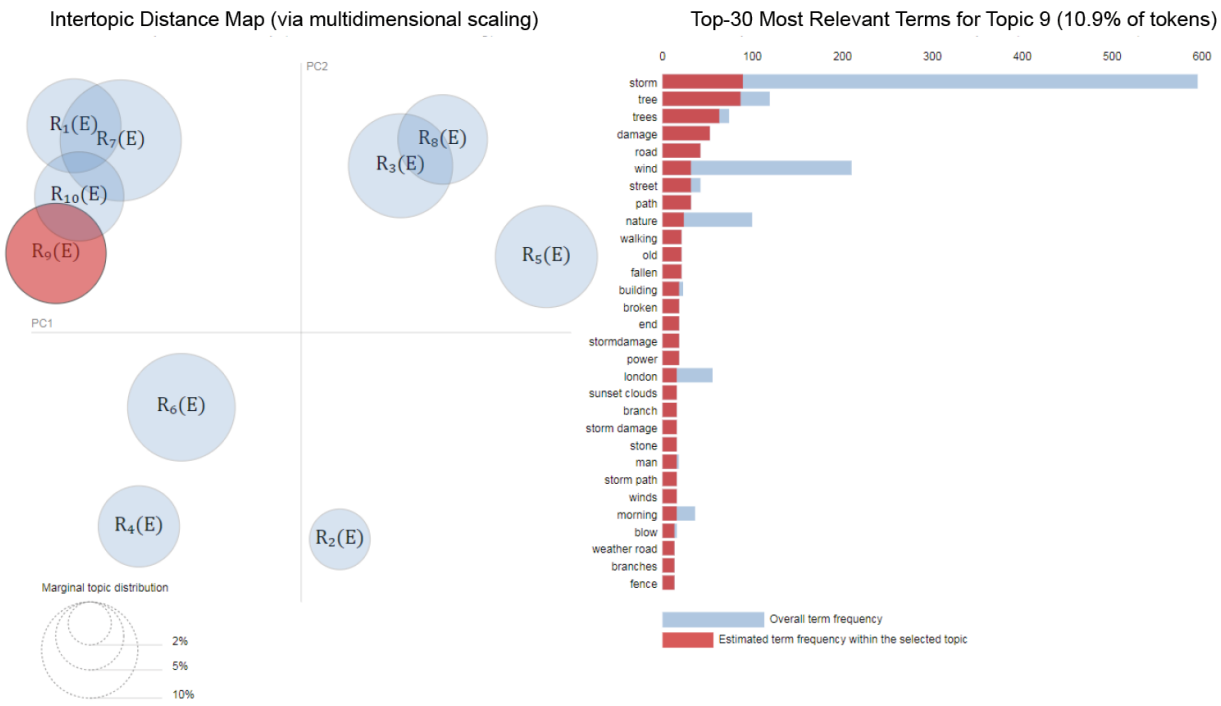

Figure 4: Interactive topic model visualization (pyLDAvis) with collective reaction $R_9(E)$ selected (damage-related topics).

In Figure 5 we project the locations of individual photographs and their topic membership back into space for selected topics. A few characteristics immediately become obvious. Firstly, the coastal topic partition $R_7(E)$ is primarily found in coastal locations. Secondly, the damage topic partition $R_9(E)$ is found along the storm's track in southern England, while topic partitions $R_1(E)$ and $R_8(E)$ are indeed associated with locations captured by toponyms in their top 10 terms respectively.

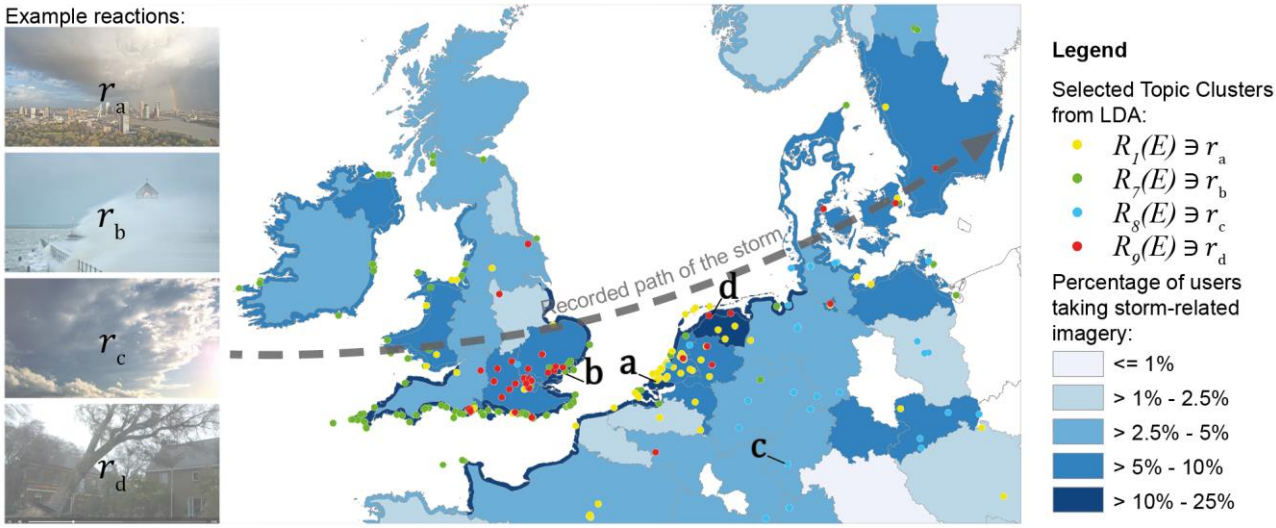

Figure 5: Percentage of total Flickr users who took storm-related imagery from October 26 to 29 (2013) per NUTS-1 area and 10 km coastal zone, and photo locations for selected Topic Clusters (LDA).

In exploring reactions, a last key question to be discussed here concerns the origin of those reacting to an event and the form of these reactions. This aspect of the Social Facet (C3) can be explored by taking into account the origin of users, which is publicly made available on Flickr profiles by 356 of the 645 users (55%). According to the location of contributed images and user home locations (country), we distinguish between reactions from two groups, locals $P^l(R(E)) = \{p_i | \, p_i.home \in s^E\}$ and tourists $P^t(R(E)) = \{p_i | \, p_i.home \notin s^E\}$, where $p_i.home$ denotes the home place of the user p_i. According to Hecht & Gergle (2010), "50 percent of Flickr users contribute local information on average, and over 45 percent of Flickr photos are local to the photographer" (p.229). For our collective reactions, we observe that 7 out of 10 clusters show ratios with more that 90% of photos taken by local population (see Fig. 3). Only $R_3(E)$ reflects a ratio that corresponds to the overall Flickr pattern, with 47% of reactions relating to local population. One possible conclusion might be that images contributed by tourists are more likely to relate to a general set of weather related

characteristics and aesthetics (e.g. collective reactions $R_2(E)$ and $R_3(E)$), which perhaps reflects an underlying behaviour pattern that is present in most reactions on Flickr. Reactions of locals, in contrast, are more likely to document unique sub-events of the storm (e.g. damage) because this group is perhaps most affected by long-term consequences (e.g. personal or economic loss). It is important to note that the increased filtering impairs our ability to accurately interpret these patterns. A thorough analysis would therefore have to take additional data into account to corroborate assumptions and continue exploration. This could include, for example, additional information from different LBSM or further background knowledge on particular sub-events of St Jude storm.

5 Conclusions

LBSM research is becoming increasingly complex with a growing number of disciplines and interests involved. We have set out a framework with regard to event-reaction-research and laid out the foundations for structured analysis of collective reactions to events. Abstracting event-reaction-relations in the basic facets of the ER-Cube forms a basis by which reactions can be characterized and aggregated. In our conceptual model, an explicit distinction is made between the definition of the referent event by the analyst (the top-down component) and the aggregation of individual reactions based on similarity measures (the bottom-up component). The two-part process ensures we can differentiate between external input (the query space) and observed data patterns (the characteristics of reactions). The proposed workflow and task matrix based on the conceptual framework aims to support a variety of perspectives and can be used to design and build applications that specifically focus on the dynamics of collective human reactions. We illustrate the use of the model and workflow using a specific example, the St Jude's storm, where the reactions take the form of tagged

georeferenced images taken by individual Flick users. Our focus is not on analysing the storm itself, but illustrating how the concept model and workflow can be applied to real data.

A primary challenge that became apparent is the uncertainty that accompanies association of reactions to a chosen referent event. While we have demonstrated one way to verify suitability, future work should focus on systematically evaluating validity, accuracy and reliability of queries. In future work we also plan to explore not only the spread of reactions using our model in more detail, but also the ways in which uncertainty in time and position related to reactions influence perception of events. For example, social media may be directly associated with coordinates, but facet dimensions also represent perspectives held by people. These perspectives influence the collective view of a particular event, and require further engaging with and making sense of what people actually mean.

6 Acknowledgements

[excluded for blind review]

7 Data availability statement

The authors confirm that aggregate data supporting the findings of this study are available within the supplementary materials. Original data can be retrieved from the Flickr API using the query provided in the work herein. The original data are not publicly available due to copyright restrictions and privacy constraints.

8 References

Allen, E., Edwards, G., & Beard, Y., 1995. *Qualitative causal modeling in temporal GIS*. Lecture Notes in Computer Science. No. 988: 397, (988), 397.

Allen, J. F., & Hayes, P. J., 1989. *Moments and points in an interval-based temporal logic*. Computational Intelligence, *5*(3), 225–238. DOI: 10.1111/j.1467-8640.1989.tb00329.x

Amanatullah, B., et al., 2013. *Temporally Aligning Clusters of Social Media Reaction to Speech Events*. Proceedings of The 2013 World Congress in Computer Science, Computer Engineering, and Applied Computing: July 22-25, Las Vegas.

Andrienko, N., et al., 2015. *Detection, Tracking, and Visualization of Spatial Event Clusters for Real Time Monitoring*. IEEE/ACM Data Science and Advanced Analytics (DSAA), 1–10. http://dx.doi.org/10.1109/DSAA.2015.7344880

Beard, K., Deese, H., & Pettigrew, N. R., 2008. *A framework for visualization and exploration of events*. Information Visualization, 7, 133–151. DOI: 10.1057/palgrave.ivs.9500165

Bell, S., 2012. *Landscape: Pattern, Perception and Process*. In Landscape: Pattern, Perception and Process. Abingdon, Routledge.

Brabham, D. C., 2013. *Crowdsourcing*. MIT Press. Available from http://www.jstor.org/stable/j.ctt5hhk3m [Accessed 9 August 2017].

Burnap, P., et al, 2014. *Tweeting the terror: modelling the social media reaction to the Woolwich terrorist attack*. Social Network Analysis and Mining, 4, 1–14. DOI: 10.1007/s13278-014-0206-4

Castillo, C., et al., 2014. *Characterizing the life cycle of online news stories using social media reactions*. Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW, 14-18 March Vancouver, 211-223. DOI: 10.1145/2531602.2531623

Chen, X., 2003. *Object and event concepts: A cognitive mechanism of incommensurability*. Philosophy Of Science, 70, 962–974. DOI: 10.1086/377381

Chen, Y., Parkins, R., Sherren, K., 2017. *Using geo-tagged Instagram posts to reveal landscape values around current and proposed hydroelectric dams and their reservoirs*. Landscape and Urban Planning.

Choudhury, M. De, et al., 2010. *How does the data sampling strategy impact the discovery of information diffusion in social media?* Proceedings of the AAAI Conference on Weblogs and Social Media, 23 – 26 May 2010 Washington, CA: AAAI Press, 34–41.

Claramunt, C., & Jiang, B., 2000. *Hierarchical reasoning in time and space*. Proceedings of 9th International Symposium on Spatial Data Handling, 1–10. Available from http://fromto.hig.se/~bjg/Clara%26JiangSDH.PDF [Accessed 9 August 2017].

Crane, R., & Sornette, D., 2008. *Robust dynamic classes revealed by measuring the response function of a social system*. Proceedings of the National Academy of Sciences, 105, 15649–15653. DOI: 10.1073/pnas.0803685105

Davidson, D., 1980. *Essays on Actions and Events*. Journal of Philosophy, 1, 0–19. DOI: 10.1093/0199246270.001.0001

Dearden, L., 2016. *Anger over "Bregret" as Leave voters say they thought UK would stay in EU*. The Independent. Available from http://www.independent.co.uk/news/uk/politics/brexit-anger-bregret-leave-voters-protest-vote-thought-uk-stay-in-eu-remain-win-a7102516.html [Accessed 9 August 2017].

Downs, A., 1972. *Up and down with Ecology—the Issue-Attention Cycle*, Public Interest, 28, p. 38.

Dustdar, S., & Rosenberg, F., 2007. *A survey on context-aware systems*. Information Systems, 2.

Egenhofer, M. J., & Franzosa, R. D., 1991. *Point-set topological spatial relations*. International Journal of Geographical Information Systems, *5*(2), 161–174. DOI: 10.1080/02693799108927841

Etzion, O., & Niblett, P., 2010. *Event Processing in Action* [online]. Available from http://dl.acm.org/citation.cfm?id=1894960 [Accessed 9 August 2017].

Fung, I. C. H., et al., 2015. *Chinese social media reaction to information about 42 notifiable infectious diseases*. PLOS ONE, 10, 1–16. DOI: 10.1371/journal.pone.0126092

Galton, A., 2006. *On what goes on: The ontology of processes and events*. Formal Ontology in Information Systems. IOS Press, 4. Available from http://www.comp.leeds.ac.uk/brandon/FOIS-06/CRC/Part-0-InvitedTalks/02_fois06.pdf [Accessed 9 August 2017]

Galton, A., 2008. *Experience and history: Processes and their relation to events*. Journal of Logic and Computation, 18, 323–340. DOI: 10.1093/logcom/exm079

Galton, A., 2015. *Outline of a formal theory of processes and events, and why GIScience needs one*. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 9368, 3–22. DOI: 10.1007/978-3-319-23374-1_1

Galton, A., & Mizoguchi, R., 2009. *The water falls but the waterfall does not fall: New perspectives on objects, processes and events*. Applied Ontology, 4, 71–107. DOI: 10.3233/AO-2009-0067

Gao, H., et al., 2014. *Modeling User Attitude toward Controversial Topics in Online Social Media*. Eighth International AAAI Conference on Weblogs and Social Media, 27–29 May 2015 Oxford, 121–130. Available from http://www.aaai.org/ocs/index.php/ICWSM/ICWSM14/paper/viewPDFInterstitial/8058/8112 [Accessed 9 August 2017].

Hahmann, S., Purves, R., & Burghardt, D., 2014. *Twitter location (sometimes) matters: Exploring the relationship between georeferenced tweet content and nearby feature classes*. Journal of Spatial Information Science, 9, 1–36. DOI: 10.5311/JOSIS.2014.9.185

Hashimoto, T., et al, 2013. *Comparison of reaction in social media after the East Japan Great Earthquake between Thailand and Japan*. 13th International Symposium on Communications and Information Technologies: Communication and Information Technology for New Life Style Beyond the Cloud, ISCIT 2013, 781–786. DOI: 10.1109/ISCIT.2013.6645967

Hauthal, E., 2013. *Detection, Modelling and Visualisation of Georeferenced Emotions from User-Generated Content*. 26th International Cartographic Conference Proceedings, 25–30 August 2013, Dresden.

He, J., et al, 2015. *Uncovering social media reaction pattern to protest events: A spatiotemporal dynamics perspective of ferguson unrest*. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 9471, 67–81. DOI: 10.1007/978-3-319-27433-1_5

Hecht, B., et al., 2011. *Tweets from Justin Bieber's heart: the dynamics of the location field in user profiles*. Proceedings of the SIGCHI conference on human factors in computing systems, ACM, 237-246.

Hecht, B., & Gergle, D., 2010. *On the "Localness" of User-Generated Content*. In: Proceedings of the ACM conference on Computer supported cooperative work, New York, pp. 229–232.

Hickey, K. R., 2014. *A review of the 2013 hurricane, tropical cyclone and typhoon season*. International Journal of Meteorology.

Kounadi, O., et al., 2015. *Exploring twitter to analyze the public's reaction patterns to recently reported homicides in London*. PLOS ONE, 10, 1–17. DOI: 10.1371/journal.pone.0121848

Kuhn, W., 2012. *Core concepts of spatial information for transdisciplinary research*. International Journal of Geographical Information Science, 26, 2267–2276. DOI: 10.1080/13658816.2012.722637

Lipizzi, C., Iandoli, L., & Marquez, J. E. R., 2016. *Combining structure, content and meaning in online social networks: The analysis of public's early reaction in social media to newly launched movies*. Technological Forecasting and Social Change, 109, 35–49. DOI: 10.1016/j.techfore.2016.05.013

Liu, Y., et al., 2008. *Towards A Spatiotemporal Event-Oriented Ontology*. Artificial Intelligence, October 2015, 18–20.

Lyons, J., 1977. *Semantics: Volume 2*. Cambridge University Press, 1, 388.

McEnery, T., McGlashan, M., & Love, R., 2015. *Press and social media reaction to ideologically inspired murder: The case of Lee Rigby*. Discourse & Communication, 9, 237–259. DOI: 10.1177/1750481314568545

Meaney, S., et al., 2016. *Reaction on Twitter to a Cluster of Perinatal Deaths: A Mixed Method Study*. JMIR Public Health and Surveillance, 2. DOI: 10.2196/publichealth.5333

Mitrou, L., et al., 2014. *Social media profiling: A Panopticon or Omniopticon tool?* Proceedings of the 6th Conference of the Surveillance Studies Network, 24–25 April 2014, University of Barcelona.

Nikfarjam, A., et al., 2015. *Pharmacovigilance from social media: Mining adverse drug reaction mentions using sequence labeling with word embedding cluster features*. Journal of the American Medical Informatics Association, 22, 671–681. DOI: 10.1093/jamia/ocu041

Nov, O., Naaman, M., & Ye, C., 2009. *Analysis of participation in an online photo-sharing community: A multidimensional perspective*. Journal of the American Society for Information Science and Technology, 14. DOI: 10.1002/asi.21278

Polous, K., Krisp, J., & Meng, L., 2012. *The Note on Event for Event Detection from Volunteered Geographic Information (VGI)*. GIScience 2012, Ohio.

Purves, R. S., & Derungs, C., 2015. *From Space to Place: Place-Based Explorations of Text*. International Journal of Humanities and Arts Computing, 9, 74–94. DOI: 10.3366/ijhac.2015.0139

Quine, W. V. O., 1985. *Events and reification*. Actions and Events: Perspectives on the Philosophy of Donald Davidson, 162–171. Available from http://www.fitelson.org/125/quine_events.pdf [Accessed 9 August 2017].

Robertson, C., & Horrocks, K., 2017. *Spatial Context from Open and Online Processing (SCOOP): Geographic, Temporal, and Thematic Analysis of Online Information Sources*. ISPRS International Journal of Geo-Information, 6, 193. DOI: 10.3390/ijgi6070193

Rodrigues, R. A., 2016. *#Femvertising : empowering women through the hashtag? A comparative analysis of consumers' reaction to feminist advertising on twitter*. Thesis. Lisbon School of Economics & Management.

Saito, S., et al., 2015. *Tracking time evolution of collective attention clusters in twitter: Time evolving nonnegative matrix factorisation*. PLOS ONE, 10, 1–17. DOI: 10.1371/journal.pone.0139085

Shatford, S., 1986. *Analyzing the Subject of a Picture: A Theoretical Approach*. Cataloging & Classification Quarterly, 6, 39-62. DOI: 10.1300/J104v06n03_04

Sievert, C., & Shirley, K., 2014. *LDAvis: A method for visualizing and interpreting topics*. Proceedings of the Workshop on Interactive Language Learning, Visualization, and Interfaces, 63–70. DOI: 10.1.1.100.1089

Daniel Sui & Michael Goodchild, 2011. *The convergence of GIS and social media: challenges for GIScience*. International Journal of Geographical Information Science, 25:11, 1737-1748, DOI: 10.1080/13658816.2011.604636

Szomszor, M., Kostkova, P., & St Louis, C., 2011. *Twitter informatics: Tracking and understanding public reaction during the 2009 Swine Flu pandemic*. Proceedings of the ACM International Conference on Web Intelligence, WI 1 August 2011 Lyon, 320–323. DOI: 10.1109/WI-IAT.2011.311

Teitler, B. E., et al., 2008. *NewsStand: A new view on news*. In Proceedings of the 16th ACM SIGSPATIAL international conference on Advances in geographic information systems, November 5–7 2008 Irvine, CA. NY: ACM, 18.

Towne, W., Rosé, C., & Herbsleb, J., 2016. Measuring Similarity Similarly: LDA and Human Perception. ACM Transactions on Intelligent Systems and Technology ACM Reference Format ACM Trans. Intell. Syst. Technol, 7(2), 25:1-25:29. DOI: 10.1145/0000000.0000000

Tsytsarau, M., Palpanas, T., & Castellanos, M., 2014. *Dynamics of News Events and Social Media Reaction*. Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, August 24–27 2014 NY. ACM, 901–910. DOI: 10.1145/2623330.2623670

Westermann, U., & Jain, R., 2007. *Toward a common event model for multimedia applications*. IEEE Multimedia, 14, 19–29. DOI: 10.1109/MMUL.2007.23

Worboys, M., 2005. *Event-oriented approaches to geographic phenomena*. International Journal of Geographical Information Science. 19, 1–28. DOI: 10.1080/13658810412331280167

Worboys, M., & Hornsby, K., 2004. *From objects to events: GEM, the geospatial event model*. GIScience, 3234, 1–17. DOI: 10.1007/978-3-540-30231-5_22

You, A., et al., 2012. *Detecting Automation of Twitter Accounts: Are You a Human, Bot, or Cyborg?* IEEE Transactions on Dependable and Secure Computing. 9, 811-824.

Zacks, J. M., & Tversky, B., 2001. *Event structure in perception and conception*. Psychological Bulletin, 127, 3–21. DOI: 10.1037/0033-2909.127.1.3

Zacks, J. M., et al., 2007. *Event perception: A mind-brain perspective - ProQuest*. Psychological Bulletin, 133, 273–293. DOI: 10.1037/0033-2909.133.2.273

Zeng, L., Starbird, K., & Spiro, E. S., 2016. *#Unconfirmed: Classifying Rumor Stance in Crisis-Related Social Media Messages*. Proceedings of the International AAAI Conference on Weblogs and Social Media, May 17–20 2016, Maternushaus, Germany: AAAI Press. 747–750. Available from http://www.aaai.org/ocs/index.php/ICWSM/ICWSM16/paper/viewFile/13075/12845 [Accessed 9 August 2017].

Zimmermann, A., Lorenz, A., & Oppermann, R., 2007. *An operational definition of context*. Proceedings: 6th International and Interdisciplinary Conference, CONTEXT August 20 – 24 2007, Denmark. Springer, 558-571.