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Emotional profiling of locations based on social media

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Abstract

Social Media is increasingly becoming an integral part of our lives and a place where an ever growing portion of our daily communication takes place. As we communicate, we reveal our emotions and this *emotional chronicle* is kept in our Social Media history. As the access to Internet became more pervasive, Social Media platforms could also store the location where the interactions took place, enabling the analysis of the emotions in these locations. Pursuing this idea, we suggest a method to create the emotional profile of a location based on the long-term emotional rating of the geo-localized SM interactions. In this paper we present our method based on a multivariate kernel density function of SM interactions on a Russell's inspired circumplex plane, explain how we extract the emotions from Social Media Interactions relying on a modified version of extended Affective Norms for English Words and validate our approach with real-life locations.

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1. Introduction

Today's digital world is unthinkable without the existence of Social Media (SM). SM has become part of our lives and a living document of our culture; even the Library of Congress is archiving all tweets sent by Americans ever since the Twitter platform went live. Lee Humphreys, a communication professor at Cornell University in New York, said that "the brief online messages -tweets- can reveal volumes about the culture where they were produced" [1].

What makes Social Media so *revealing* –unlike other channels– is the fact that users are less reluctant to express -almost in a unfiltered way- what's literally going through their minds ([1]) –with the exception of work-oriented and other specific purpose platforms,such as LinkedIn–. And no matter how empty of content a message seems to be, each and every SM interaction encapsulates a piece of communication with an underlying intent. A SM interaction can be seen as the result of basically two choices made by the author: the *what to convey* and the *how to transcribe it in words* -or other richer assets, such as pictures, videos, etc-. Even the SM specific forms of interaction, such as the famous Facebook "like" or Twitter "favourite" or "retweet" are full of meaning.

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[1] "http://www.businessinsider.com/library-of-congress-is-archiving-all-of-americas-tweets-2013-1"

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In the last recent years, researchers have developed sophisticated machine learning methods to estimate or extract emotions from user generated content, including support vector machines ([2]), maximum entropy approaches ([3]) and concept-level analysis of natural language text ([4]) supported by combinations of common-sense-reasoning and ways of representing affection -e.g.: affective onlogies ([5]), etc-.

In Social Media in general and in micro-blogging platforms in particular, the length of the interactions –typically short– on one hand and the disconnection of subsequent interactions on the other hand compromise the utility of these methods, that require a decent amount of high-quality text. To overcome these limitations, alternative approaches leveraging dictionaries have been explored. A popular one is the ANEW (Affective Norms for English Words) [6], created in a crowd-sourcing way where random people were asked to read a corpus and to provide a Self-Assessment Manikin rating ([7]). for each occurrence of a term in the predefined set of 1034 English words. For each word, ANEW provides 3 statistically normalized -mean and standard deviation- ratings for all three PAD emotional state model components created by Mehrabian et al. [8] back in 1980. These components are *(P)leasure* or valence –the pleasantness of the emotion–, *(A)rousal* –the intensity of emotion provoked by the stimulus– and *(D)ominance* –the degree of control exerted by the emotion–. For example, boredom is an unpleasant emotion with low arousal and low dominance... anger is unpleasant, with high arousal and high dominance. With complex emotion representation models like the one suggested by J. Russell in 1980 [9], the valence, arousal pair can be mapped to particular emotions or moods.

The advent of internet mobile and wireless technologies -such as UMTS and WiFi-, enabled a new way of interacting with the SM channels. The user could consume SM feeds and post updates from everywhere –provided there was no connectivity issue–. Increasingly, the location where the interaction took place became an integral part of the SM communications. Traditional SM platforms started supporting the geo-location of SM interactions and even new platforms emerged, where the content completely disappeared in favour of the location -e.g.: Foursquare [2]-. As a side effect, an ever increasing volume of SM content and users started being associated to a particular geographical place. The analysis of these users and this content reveals insights about the location that weren't feasible before.

In our paper we want to exploit the potential of combining these two ideas: extracting emotions from SM interactions and the possibility of gaining new insights for locations using geo-localized SM interactions. Thus, the purpose of this piece of work is defining a method to quantify the emotional baseline of a given location based on the SM user generated content attached to this location.

Understanding the emotional profile of a location could change the way local campaigns are run. Marketing messages can be tailored to address the predominant emotions on a location to maximize their effect. A political campaign can also benefit from these insights to choose the most effective wording for local communities. At a particular level, a person might be also interested in understanding how good his/her personality matches the emotional profile of a potential place to move to. These are just a few examples of the countless applications of the output of this paper.

We organized this paper starting off with the background information for our research. Then, the method for establishing the emotional profiles and the metrics for measuring emotional impact are introduced. After that, we present system that implements our metrics and then we show some practical examples of emotional profiling of locations. Finally, we share our conclusions and point out future work on this topic.

2. Background and related work

The first attempts to create a model to compare emotional states took place in the psychology research domain. At early stages, emotional states were represented in different scales for the emotion intensity, degree of pleasantness, exerted control, etc. Based on the work initiated in [10] and [8] where the *Pleasure-Arousal-Dominance* (PAD) model was formally introduced, Russell suggested in a seminal work the combination of emotional axis to create a circumplex model that enabled the position of emotions on a plane [9]. An emotional state was represented as a pair of coordinates: on the x-axis the valence and on the y-axis the arousal of the stimulus. Up to 28

[2] `https://foursquare.com`

emotional states have been multidimensional scaled in Russell's model, so that intermediate terms are polar opposites (e.g.: excited-depressed, distressed-relaxed, etc). A set of new models and refinements on Russell's model followed, each one conceptualizing the dimensions in different ways: positive and negative affect [11], tension and energy [12], approach and withdrawal [13], etc.

In 1999, Bradley and Lang created a set of normative emotional ratings for 1034 commonly used English words, also known as the set of Affective Norms for English Words or ANEW. For the first time, this work made possible to quantify natural language text fragments in terms of PAD model dimensions [6]; in other words, it can be considered the enabler for the emotional states extraction from user generated content. The ANEW set was extended to over 13K lexemes and faceted by gender and education level in [14] and adapted for other languages in other languages ([15],[16],[17]).

In the recent literature we find countless approaches to extracting emotional states from user generated content. In [18], the authors went even further and mapped the emotions to a 3D virtual human. Additionally, the same authors provided a color interpretation of the emotions mapping different values of arousal and valence to colors. In [19] a predictive model for blog posts ratings providing the estimated level of valence and arousal of a post on an ordinal scale was presented, also taking as a basis the Russell's circumplex model. [20] created an interactive tool to visualize the emotions extracted from a Twitter query over the Russell's 2D plane for the most recent time. This tool also allows for a keyword extraction based on frequency, as well as the visualization of a moods' heatmap over time. In [21] the authors explored the role of the different emotional states in the information diffusion in SM. In [22] the authors explored the emotions distribution of the BBC forum.

Geo-localized Social Media interactions have been leveraged in several works to augment the knowledge about the location where they have been created. In [23] the authors suggest a set of metrics to quantify the impact of a topic in different locations. In [24] the authors explored the use of geo-localized SM insights for customers' acquisition and retention campaigns. In the area of disasters prevention, geo-localized interactions have been intensively analysed to create early warning and prediction systems on natural catastrophes such as earthquakes, tsunamis, etc. in particular locations [25, 26, 27]

3. Defining the emotional profile of a Location

In this section we proceed with the formal definition of our approach for measuring the emotional impact of an event on a particular location.

3.1. Preliminary definitions

To support the metrics definition in our methodology, we first introduce a set of relevant concepts:

Definition 1. *The set U represents the set of social media users from which we have evidence they have been in the location L we are monitoring during the time period under analysis* $\triangle t$

$$U \equiv \{u\},\ \forall u_i \in U,\ InLocation(u_i, L, \triangle t) \tag{1}$$

Definition 2. *The Social Network for a given user* u_i *is defined as:*

$$SN\,(u_i) \equiv \{u\},\ \forall\ u_j \in SN(u_i),\ Follows(u_i, u_j) \tag{2}$$

$Follows(u_i, u_j)$ is a function representing a SM connection between the users u_i *and* u_j, so that u_i is exposed to the SM content generated by u_j. $Follows(u_i, u_j)$ is not always symmetric; although in several SM platforms it is the case (e.g.: Facebook or Linked.in).

Definition 3. *The set* $SN(U)$ *represents the set of all the users being followed by the users in* U*:*

$$SN(U) \equiv \{u\},\ \forall u_i \in SN(U),\ \exists u_j \in U\ |u_i \in SN(u_j) \tag{3}$$

Definition 4. *We define all user interactions* ($Interactions$) *for a given user* u_i *over a time interval* $\triangle t$*, as:*

$$Interactions\,(u_i, \triangle t) \equiv \{it\},\ \forall it_i \in Interactions\,(u_i, \triangle t),\ Author(u_i, it_i, \triangle t) \tag{4}$$

A Social Media Interaction represents the atomic piece of content generated by the user u_i during the time $\triangle t$ in a Social Media Platform (e.g.: a tweet, a re-tweet). Thus, $Author(u_i, it_i, \triangle t)$ is a function that retrieves $True$ if u_i created the interaction it_i in the time period $\triangle t$, and $False$ otherwise. The time interval t might be measured in weeks, days or hours, depending on the use case and consists of two extremes: $t\_startdate$ and end date $t\_enddate$.

We call $activeInteractions$ to those made by any user $u_i \in U$ in the location and $passiveInteractions$ the ones made by any user $u_j \in SN(U)$ the users in the location are exposed to.

An SM interaction it_i can be also seen from the Natural Language perspective as a set of terms $terms(it_i)$: $it_i \equiv \{t\}, \forall t_j, t_j \in T$ where T represents all possible terms in the English language, including spelling mistakes, newly invented terms and whatever communication unit which conveys a meaning between the sender and at least one of the recipients.

3.2. Modelling emotions on a Location

We provide now a set of definitions to formally describe the emotional state Pleasantness-Arousal-Dominance model in the SM context.

Definition 5. *We define the emotional rating ER of a user interaction it_i as a vector with three components: valence v, arousal a and dominance d*

$$ER(it_i) \equiv [v, a, d] \tag{5}$$

To obtain the values for valence v or pleasantness, arousal a and dominance d, our approach relies on a set of aggregated rating functions defined on top of the extended version of the ANEW lemmatization (eANEX) ([14]). Each PAD component in the vector is obtained applying a function that looks up the interaction lexemmas in the eANEW dictionary, retrieves the rating values for each available one and combines the results into a single value with a weighted average operation. As the eANEW also provides for each rated lexemma the standard deviation for all the rating users, we use the maximum probability value assuming a normal distribution as the weight for each lexemma $f_{max} = \frac{1}{\sigma\sqrt{2\pi}}$ to give higher weight to rating with lower sparsity.

Thus, a generic rating function is defined as follows:

$$r(it_i) = \frac{1}{\sum_{j=1}^{|terms(it_i)|} f_{max}(t_j)} \sum_{j=1}^{|terms(it_i)|} \rho(t_j) * f_{max}(t_j),\ t_j \in terms(it_i) \tag{6}$$

where $\rho(t_j)$ can be the eANEW valence mapping $\upsilon(t_j)$ to obtain v, or the eANEW arousal mapping $\alpha(t_j)$ to obtain a or the eANEW dominance mapping $\delta(t_j)$ to obtain d.

To translate the values of v, a, d to named emotional states, we make use of the enhanced adaption of Russell's circumplex model as showed in Fig. 2, which only rely on 2 components, valence and arousal.

Definition 6. *We define the emotional profile EP of a location L over a given period of time $\triangle t$ as a valence-arousal-dominance distribution resulting from the aggregation of all interactions' emotional ratings authored by the users in the location during the period of time $\triangle t$*

$$EP(L, \triangle t) \equiv [v, a, d] \tag{7}$$

where $[v, a, d] = \mathfrak{I}(ER(it_j)), Author(u_j, it_i, \triangle t), u_j \in U, InLocation(u_j, L, \triangle t)$ The function $\mathfrak{I}$ can be designed to give more weight to interactions more recent in time, to simulate potential personality changes in individuals.

To model the distribution of emotions in the emotional plane, we suggest a multivariate kernel density function ([28]), defined as follows:

$$\iota_H(x) = \frac{1}{n} \sum_{i=1}^{n} K_H(x - x_i) \tag{8}$$

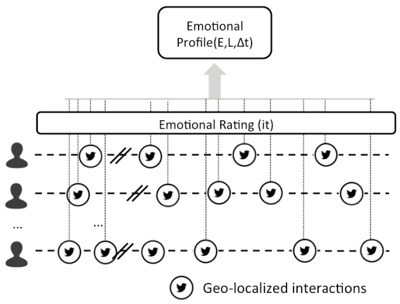
$x = (x_1, x_2, , x_d)^T, x_i = (x_{i1}, x_{i2}, , x_{id})^T, i = 1, 2, , n$ are the ER vectors; H is the bandwidth (or smoothing) matrix (chosen as described in [29]); K is the kernel function which is a symmetric multivariate density; $K_H(x) = |H|^{1/2} K(H^{1/2} x)$

An additional implementation for emotional baseline $EP(L, \triangle t)$ could be coupled to time chunks to incorporate the seasonality effects. The time granularity level depends on the variability for the particular location. Thus, one could create a baseline for a given *month of the year* -e.g.: December because of Christmas is different than February in places where Christmas is important... or the Ramadan month vs. an ordinary one in Islamic countries, etc-, *day of the week* -e.g.: a Monday vs. a Friday- or even *hour of the day* -eg.: 10:00h vs. lunch time-.

Once we have formally defined the emotional profile of a location L over time, we need to introduce an additional concept to support an important number of use cases. In order to make the emotional profiles of two different locations or the emotional profiles of the same location in different time periods comparable, we need to make use of a difference operation. As we employed multivariate kernel density functions for modelling $EP(L, \triangle t)$, to quantify the difference we suggest applying the standard deviation of the resulting difference distribution: $\sigma(|EP(L_1, \triangle t) - EP(L_2, \triangle t)|)$ or $\sigma(|EP(L, \triangle t_1) - EP(L, \triangle t_2)|)$.

4. System Architecture

The specified metrics are platform agnostic. Our system relies on Twitter because of the ease of information extraction, the text-based content dominance vs. other platforms focused more on rich media and the high share of geo-localized interactions. In order to provide speaking names for the different emotional states, the system also focuses primarily on the valence and arousal components, as the mapping to named emotions is only available for these two dimensions. The technological footprint has been adapted from [30].



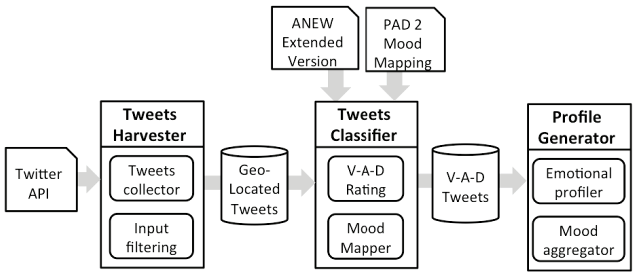


Fig. 1: (a) Emotional Impact metrics orchestration (b) System architecture overview

The system basically polls the geo-located tweets from the publicly available Twitter Search API [3] , applies the eANEW emotional rating of the content and builds the emotional profile for the location as described in the previous section. The system consists of 3 different modules in charge of different labours all along the process (see Fig. 1 (b))

Each module consists of a set of components with a clearly defined function. In the following sections we are going to describe how the different modules work and what the role of the components being involved is.

4.1. *Tweets harvester*

The harvester collects all tweets created in a given area. An area is defined in our systems as a pair of geographical coordinates –latitude - longitude– and a radius. This module also applies a language filter to avoid the later emotional rating of non-English tweets, as we are working with the eANEW.

4.2. *Tweets classifier*

This module takes care of the emotional rating of the harvested tweets as well as the mood flagging, which is carried out by two components. The *V-A-D rating component* lemmatizes the content of each tweet, performs the eANEW lookup and applies the weighting averaged defined in the Equation 6, providing a value for the valence,

[3] Available at `https://dev.twitter.com/docs/api/1/get/search`

arousal and dominance. Some constraints can be applied to avoid volatile results when for example just one lemma out of the entire tweet content is found in the eANEW file. In this case, the system for example produces an NA. Prior to the lemmatizion we apply a set of NLP components such as a sentence tokenizer followed by a word tokenizer (based on [31]) both adapting the Punkt Tokenizer [32] and a stemming algorithm to remove stop words. The *Mood mapper* assigns an emotional state to the resulting $[v, a]$ pair, applying a pre-defined moods mapping file (see [19]). Basically, it applies a refinement of the Russell's circumplex emotions model. Each interaction represented by a pair of $[v, a]$ values is assigned to the Mood label whose circumplex coordinates are the closest to these $[v, a]$.

The result of applying the Tweets classifier is a set of tweets, each one with a $[v, a]$ score and a *mood* assigned.

4.3. Profile Generator

After the emotional rating and mood flagging of the harvested SM interactions, this module aggregates the results into a location emotional profile. The *Emotional Profiler* extracts a kerned density function (see Equation 8) in the $[v, a]$ dimensional space with all $[v, a]$ ratings obtained from the previous steps. This function represents the emotional profile of the Location L, as explained in the Subsection 3.2. The *Mood Aggregator* provides an aggregated view of the flagged moods collected over the time period in terms of absolutes and share.

The system we just described can be easily adapted to work with other languages. It would require adjusting the *Input filtering*component in the *Harvester* and replacing the Affective Norms definition file for English by the one of the target language in the *V-A-D Rating* component in the *Profile Generator*.

5. Evaluating our approach to extract emotional profiles for locations

In this section we are going to show how our emotional profiling behaves for 2 different locations. We set up 2 harvesters in the two major London airports: Heathrow ($51^o28'12$", $-27'14$") and Gatwick ($51^o9'13$", $-10'55$") with a radius of 5 km respectively. Between the 23rd of November 2013 and the 23rd of January 2014, the harvesters collected a total of 852319 SM interactions. Both the period of time and the selected locations give room to several events with different emotional connotations –pre-Christmas time, New Year's Eve, massive delays and service disruptions due to weather conditions, etc–. We are going to conduct our evaluation inspecting the metrics behaviour in a set of identified scenarios.

We start with the *General emotional profile* for the locations: Fig. 2 shows the plotting of the emotional profile for both airports in Dec. 2013. We can see certain similarities, like the centering on a pretty neutral area with certain positive valence skew and slightly negative arousal (low excitement). This can be assumed to be the norm. Both locations present some activity in the *Apathetic-Worried* region. Heathrows profile is more condensed but with a noticeable *Passionate* states and a few yellow spots in the positive / positive direction. Gatwick is broader and has a more consolidated presence in the *Amused* to *Interested* space. Additional yellow spots can be also seen in the negative valence - positive arousal.

Let's have a closer look now to one event that changed the emotional profile of the impacted location: In Fig. 3(a) we can see the emotional change motivated by the service disruption in Heathrow on Jan. the 17th 2014 [4]). The usual emotional region is no longer recognizable and 3 focuses emerged in around *Expectant-Passionate*, *Melancholic-Pensive* and *Distrustful*. Obviously, Gatwick has not been impacted that hard.

In order to show the sensibility of hour approach, we shorted the profiling time to just one hour and created what we called the *emotional heartbeat* for the locations under analysis. For 10 days (20th to 30th Dec), we plotted the emotional profile kernel density function for each hour of the day with a second between plots, simulating a heartbeat. The results can be seen under this URL [5]. On Christmas day, we spot an unexpected emotional shift towards negative valence - positive arousal, atypical for a festivity. The explanation is not other but the service disruption due to weather inclemencies resulting in many passengers stranded [6]. Unusual moods for the Gatwick

[4]http://www.bbc.com/news/uk-25785804
[5]https://vimeo.com/122473636
[6]http://www.bbc.com/news/uk-england-sussex-25503513

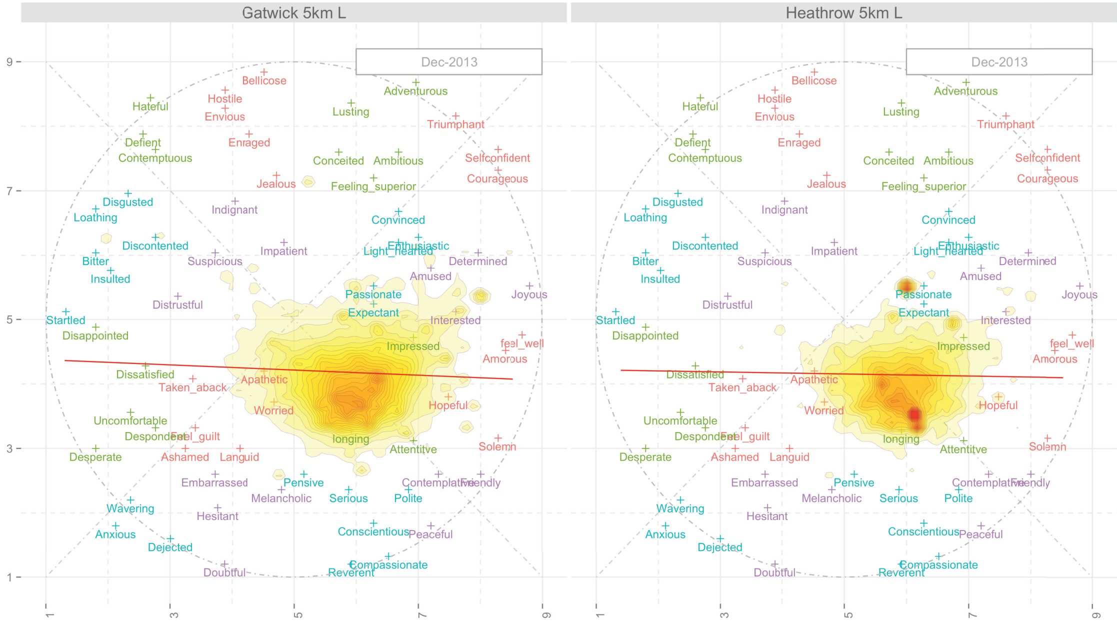


Fig. 2: Emotional Profile for Gatwick and Heathrow in Dec. 2013

emotional profile, such as *insulted, impatient, distrustful* and *suspicious* manifest. In Fig. 3 (b) this effect can be seen, but much better in the video for the hours 15:00, 16:00, etc.

To demonstrate the capability of tracing single named moods, we displayed in Fig. 4 (a) the change over 5 days of the single moods in Gatwick Airport. What we see correlates with the 2D charts we've been discussing so far: dominance of *longing* and a few moments of *Worry* , *Expectation* and *Hope*.

Lastly, we want to demonstrate the ability of monitoring emotional changes over time, for which we created the emotional profile of both airports for the entire period of time for then compare the daily emotional profile against. The chart in Fig. 4 (b) shows the results: Heathrow is emotionally more changeable than Gatwick during the period of time under analysis.

6. Conclusions

In this paper we present our approach to define emotional profiles for a location based on the analysis of Social Media interactions that have been geo-located in this location. Our method builds upon of following components: a) the well-established (P)leasantness or (V)alence-(A)rousal-(D)ominance emotional state model introduced by Russell, to model emotions, b) an extended version of the Affective Norms for English Words, to extract emotions from the Social Media user generated content and c) an evolution of the Russell's circumplex model to map the $[v, a]$ scores to one of the 28 named emotional states derived from , such as *Impatient, Hopeful, Amorous, etc.*

The emotional profile of a location is basically defined by the multivariate kernel density function applied to the whole set of $[v, a]$ scores gathered over the define time period. As an add-on to this quantification, we provide a mood synopsis or an overview of the named mood distribution during the period of time under analysis. To make the newly defined concept more useful, we also provide a difference function to track the emotional change over time on a location or to compare emotional profiles of two different locations.

To evaluate our approach, we implemented a system based on Twitter and discussed the results in different scenarios for two known locations: Gatwick and Heathrow airports. Our modelling approach seamlessly reflects different mood changes and works well even with finer time granularity (hourly chunks), as discussed in the evaluation section and proves to be very useful to support real applications.

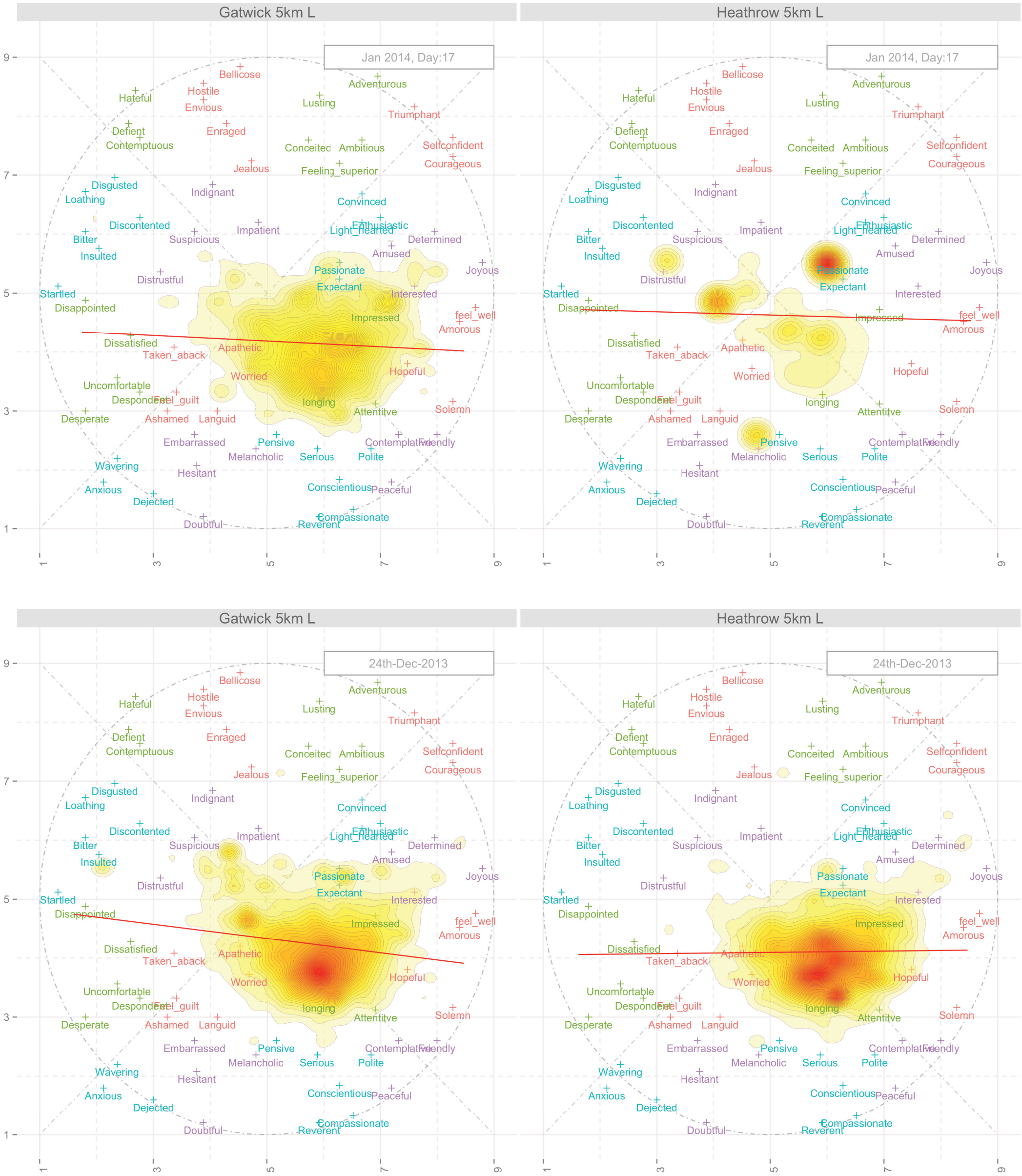


Fig. 3: (a) 17th Jan 2014 - Disruption due to flood chaos in UK South-East mostly impacting Heathrow (b) 24th Dec 2013 - Delays in Gatwick

The applications of emotional profiling in the industry are countless: from changing the way marketing messages are tailored depending on the emotional profiles for certain areas, to mental diseases prevention, to violence proneness modelling, etc.

Taking it forward, we clearly see 2 areas for future research: adopting a user centric approach –for example, creating emotional profiles of users over a longer period of time, which then are mapped to locations for better consistency or considering the segmentation by gender and educational class already present in the extended ANEW – and bias removal to make the insights representative for the entire population of a location, not just the geo-located Social Media users.

Fig. 4: (a) Named mood mapping over time (b) Emotional Profile Comparison Baseline vs. daily in both locations (Heathrow red, Gatwick cyan)

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