Sentiment Analysis

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Glossary

Attribution theory A body of theory that explains how people use information to explain the causes of events or behaviors.
Corpus A collection of a particular type of object, especially of texts.
Lexicon A dictionary that includes all of the meaningful units in a given language
Machine learning A type of computer algorithm in which the computer learns (generalizes) from experience (examples).
Message judgment approach An approach to understanding facial expressions that focuses on understanding the overall meaning of the facial configuration.
Schema A structure for organizing categories of information and any relationships between these categories.
Sign judgment approach An approach to understanding facial expressions that focuses on the individual physical movements of the face rather than the overall meaning of the facial configuration.

Since the 1990s in geography and within the social sciences and humanities broadly there has been an increase of interest in emotions and how they are entangled with people and places. This interest is perhaps hardly surprising given emotion's importance in shaping human behavior, experience, and thinking. Studies of places, the sites of lived experience, that do not consider emotional experiences shortchange our geographical understanding of the world. Emotion is fundamentally a bodily as well as a psychological phenomenon, and critical geographic perspectives such as feminist geography have highlighted the importance of the body in shaping relationships between people and places.

Emotion is strongly connected to place. Researchers and practitioners in areas as diverse as urban planning, architecture, tourism development, marketing, and policing and public safety are interested in how places make people feel and how people feel about places, both when they are in-place and from afar. In the past, emotions and their connections to places have been relatively difficult to study, requiring time- and labor-intensive methods such as interviews to obtain rich data, while methods such as questionnaire surveys introduce problems of imperfect memory of emotion into the collected data. In today's always-connected world, researchers now have a range of real-time sensor and data streams that can be accessed to understand a person's emotional response to a place while they are in location, including video and social media posts.

Emotions

Definition and Terms

The oft-quoted statement that everyone knows what an emotion is as long as they do not have to define it is reflected in the scientific literature. The enormous number of definitions of emotion might be an indication that the concept is still not fully understood despite the fact that scientific emotion research has been conducted for more than 100 years. The majority of definitions describe emotion as a complex phenomenon. Their explanation is complicated since emotional experiences can be reported by humans only with difficulty and yet the measurement of brain waves or of the nervous, respiratory, circulatory, and adenoid systems also do not describe emotions completely. A comprehensive definition of emotions needs to cover the following three aspects:

- the experiencing or sensing of a feeling (i.e., an inner arousal that is more or less consciously experienced as either pleasant or unpleasant)
- the processes happening in the brain and in the nervous system
- emotion's often observable expressions in the body (like gestures and facial expressions)

Another important aspect of emotion is the high ego-involvement of the individual.

A classical view of emotion, the so-called "basic emotion" theory, proposed that there is a small set of emotions that are felt by all people (like surprise, anger, or happiness). These "basic emotions" can be felt without interacting with others. Other emotions require interaction with other individuals, like shame, feelings of guilt, or pride. According to basic emotion theory, such emotions are differentiated and reshaped over the course of a lifetime by socioenvironmental influences and culture. Recent research challenges the "basic emotion" theory and proposes that the experience of emotions requires an emotion schema, that emotion schemas vary across cultures and individuals, and that their use requires an understanding of context.

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Other emotion-related terms include “sentiment,” “feeling,” and “affect.” These terms are often used as synonyms but are in fact distinct concepts. Sentiments are enduring, less intense, diffuse emotions that are not related to particular internal or external events and that can influence cognitive processes like perception, information processing, and memory. The term “feeling” means the experience-related aspect of an emotion, that is to say, the interpretation of the conscious and subjective experience of an emotion. The concept of affect in English is often used as a hypernym for mental processes, emotions, sentiments, and also for attitudes. Less often, affect means merely the valence of experiences in the sense of pleasure and displeasure or positive and negative subjective experiences. In German, affects are brief, sudden, and intense feelings of convergence or rejection, that are barely controlled cognitively. Due to the possibility that all these terms are closely related, a clear demarcation is not feasible in every case. The occurrence of a given feeling can be accompanied by sentiments and sensations.

Emotion Theories

Emotions are extraordinarily complex processes and the processes governing their emergence are still heavily debated. The different approaches for explaining the occurrence of emotions can be reduced to one fundamental question, which is also referred to as the Zajonc–Lazarus controversy: are cognitive processes independent of emotions or not? Thus two kinds of theories can be distinguished: biologically- or physiologically oriented ones on one side, and cognitive ones on the other side (Fig. 1).

Biologically oriented theories are grounded in the assumption that a stimulus evokes a physiological reaction called a feeling. For example, after a stimulus is recognized (e.g., a wild bear), it leads immediately to visceral changes (e.g., accelerated heartbeat) and motor reactions (e.g., running away) that are then perceived subsequently as an emotion (e.g., fear). These theories remain controversial: the same visceral changes can be associated with different emotions (for example, we can cry because of sadness or joy) and the simulation of visceral changes (such as with adrenaline injections) does not induce “real” emotions.

Cognitive approaches originate from attribution theory. According to these approaches, individuals correlate states of inner arousal with plausible causes, with the result that different emotions arise depending on the situation or the person’s interpretation of a situation. In other words, a physiological arousal has to exist, but it also has to be interpreted subjectively. If one of the two factors is missing, the emotion is incomplete or is not even noticed.

In conclusion, in the cognitive approaches, people are assumed to appraise the situation before they notice their state of arousal, and the knowledge from this appraisal affects their interpretation of the emotion, whereas with the biological approaches, it is the opposite—the state of arousal is noticed first and then interpreted as an emotion.

Structuring Emotions

The definition of emotions allows a distinction between emotional and nonemotional states as well as a structure for characterizing emotional states. Approaches for structuring emotions can be distinguished into dimensional and differential.

Dimensional approaches try to reduce emotional states to a few dimensions (Fig. 2). Each emotion can be described as a combination of different intensities of these dimensions. Research in this paradigm uses one of two main approaches: either a two- or three-dimensional model. In almost every case, one dimension describes the valence of emotions (ranging from negative to positive, or unpleasant to pleasant); however, there is disagreement on how to characterize arousal (i.e., the inner excitement), which is regarded as either one- or two-dimensional. While some researchers consider one dimension of arousal to be sufficient to describe emotions in combination with the valence dimension, other researchers believe their empirical results suggest there are two distinct arousal dimensions. The three-dimensional models propose one valence and two arousal dimensions, though the terms differ between the models. The two arousal dimensions are variously described as potency and activity, dominance and arousal, or activation and tension. Nevertheless, these models are in many ways similar constructs despite diverging denotations.

In contrast to dimensional approaches, which try to characterize emotions using a few global dimensions, differential approaches emphasize the subjectively experienced qualities of emotions that are distinguishable. In these approaches, emotions are structured according to complex similarities. These similarities can be defined by the spectrum of emotional qualities in “basic emotions” or by statistical methods based on subjective appraisals.

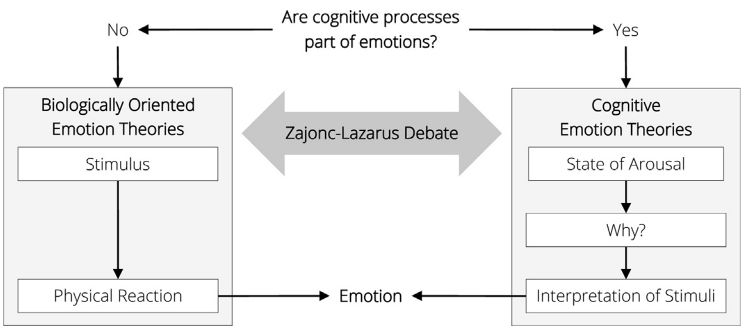

Figure 1 The two kinds of emotion theories.

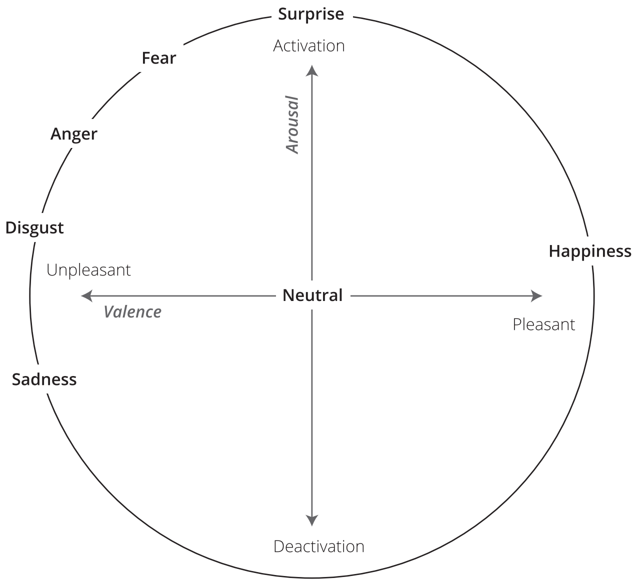

Figure 2 One commonly used dimensional approach to characterizing emotions, the circumplex model. The location of the six "basic emotions" within the two dimensions is depicted in this model. Adapted from James A. Russell and Lisa Feldman Barrett, "Core Affect, Prototypical Emotional Episodes, and Other Things Called Emotion: Dissecting the Elephant," *Journal of Personality and Social Psychology*, 76, 5, 805–819, 1999, Published by the American Psychological Association, adapted with permission.

Approaches that focus on the subjectively experienced qualities of emotions assume that all emotions can in fact be derived from combinations of "basic emotions," which are sometimes described as primary emotions. These derived emotions are called secondary emotions. Variations within these approaches derive from different rationales for the choice of which emotions are "basic emotions": among others, universal facial expressions are identifying criteria. Established approaches show great heterogeneity in their results: the quantity, kind, and quality of the proposed primary emotions vary strongly among approaches.

Approaches that focus on the similarity of subjective appraisals try to structure emotions according to the subjective similarity of their experience or according to common linguistic usage. Thus they use empirical similarities as a basis for category creation instead of theoretical considerations.

Capturing Emotions

A wide range of measurements can be made in an attempt to characterize emotional experiences, including the following:

- physiological responses (cardiovascular, respiratory, electrodermal)
- tonic posture responses (tension and relaxation of the body)
- instrumental motoric responses (e.g., biting, hitting, fleeing)
- expressive motoric responses (gestures, countenance [facial expressions], paralinguistic events)
- expressive linguistic responses (syntactic and lexical selection, stylistic varieties)
- subjective experience responses (the feelings that everyone experiences while having emotions)

These responses can be used to characterize emotions with the help of different procedures. Requesting emotions is a verbal procedure but has the disadvantage that verbal statements about emotions are often difficult to access, not sufficiently detailed, are made after experiencing the emotion rather than contemporaneously, and might be manipulated or filtered by the respondent. Emotions can also be characterized from expressive linguistic responses that were made spontaneously—that is, those that were not made in response to a request from a researcher but in the course of everyday activities.

Nonverbal procedures include explicit emotion measurement as well as physiological measurement. In explicit emotion measurement, emotional states are classified by the respondent using a scale, but this procedure requires a certain amount of training by the respondent. Physiological measurements are used to infer a scalar value of emotion from a physiological measurement. The advantage of physiological measurements is that the respondent does not have to interpret and report their emotions. For researchers, interpreting a meaning from physiological measurements is typically difficult because a given individual may externally express an emotion in different ways at different times, depending on the context. However, the method does enable the real-time capture of information about emotions.

Two methods for characterizing emotions (corporeal and linguistic responses) provide the advantage that they can be used to observe emotions unobtrusively, making it less likely that the emotions are manipulated or filtered by the respondent.

Analysis of Corporeal Emotional Responses

Emotions in Bodies

Some research approaches assume that emotions can be characterized from faces and from other measurements of the body such as the skin's electrodermal activity (EDA). One EDA measure that is commonly used is galvanic skin response (GSR). GSR has been used to evaluate emotional responses to different places as well as to representations of places (e.g., maps). By applying small sensors to a person's body, GSR can identify when there are changes in electrical conductance, indicating an emotional response. The method is sensitive in that it can identify small changes in electrical conductance. GSR sensors are applied to areas of the body that are known to have large numbers of sweat glands, such as the hands. The measure is limited in that it can only measure the arousal dimension of an emotional response, and it does not provide information about whether that arousal stems from a positive or negative feeling. When used as a singular measure, it cannot be used to identify which emotion(s) a person is feeling.

Facial expression recognition technologies are another method that is used to try to identify the types of emotions a person is expressing, but they provide less precise information about the arousal dimension of emotions than does GSR. Some researchers have criticized these methods because a given facial expression can be associated with more than one emotion and vice versa. Facial expression recognition technologies first capture video of a person's face and then identify which emotions are expressed by classifying facial configurations. There are also more sophisticated ways of analyzing facial data using 3D cameras. High-quality 3D sensors embedded within virtual reality headsets can detect subtle facial expressions such as the slightest movement of an eyebrow or the slight downturn of the lips. Standard video is less able to capture small differences in facial expressions and is more sensitive to lighting-related problems than are 3D sensors. 3D sensors can measure subtle expressions as well as account for when the person moves and is no longer directly facing a single camera. As new technologies such as augmented reality and virtual reality (AR/VR) become more commonly used in geography research, some researchers have proposed that facial expression recognition will be useful for supporting multimodal, fully immersive experiences that adjust and react to participants' emotional states.

Facial Expression Recognition

There are two primary approaches that researchers use to recognize emotions from facial expressions: facial affect inference and facial muscle action detection. Facial affect inference is a message judgment approach while facial muscle detection is a sign judgment approach.

Technologies that use the message judgment approach identify prototypical facial expressions that relate to particular emotional states. These are often called "discrete emotions." For instance, the algorithm will identify that the sides of your mouth have turned upwards and your eyes were squinting; two features that together are believed to indicate happiness. Often, the emotions these technologies are designed to recognize are the six "basic emotions" that are proposed in the basic emotion theory: anger, happiness, surprise, disgust, sadness, and fear. Discrete emotion recognition does not work well when the individual's face is out of plane or displays a mixture of emotions.

The sign judgment approach focuses on facial "Action Units" (AUs). This approach monitors the actions of individual muscles in the human face, finding the smallest discernible movements of those muscles. There are 9 AUs in the upper face, 18 in the lower face, and 5 that are neither upper nor lower—for a total of 32 AUs. There are also 11 descriptors of head position, 9 for eye position, and 14 for other, nonclassified AUs. Together, these AU combinations can be interpreted as different types of emotion. Unlike discrete emotion recognition methods, there are many ways in which to interpret these signs, including as indicative of one of the six "basic emotions" or as other, more complex emotions.

Both the sign judgment and message judgment approaches use two types of facial expression attributes to characterize facial expressions: appearances and geometric features. Appearances include the face's textures such as wrinkles and furrows. Geometric features are composed of the shapes of features within the human face, such as how the eyebrows or mouth are shaped during an expression. Geometric-feature-based approaches often use active appearance models (AAMs), which are a set of points overlaid on an image or video of a face and that is used to measure changes in particular facial features, e.g., movement of the corners of the mouth.

Classification Methods

Facial expression recognition methods often use machine learning algorithms to classify facial expressions. These techniques include both supervised and unsupervised approaches. Ultimately the goal of classification is to detect and differentiate between different emotions from facial expression attributes.

Supervised machine learning techniques follow a common sequence: feature selection, classification, and emotion extraction. In the feature selection stage, it is necessary to choose facial expression attributes for training the machine learning algorithm. For instance, a human identifies particular facial expression attributes that accompany an emotion within a small set of images that serves as the training dataset, thereby building a set of attribute-emotion relationships. In the classification stage, the algorithm classifies features using these trained attribute-emotion relationships with the help of a statistical method. Finally, each video segment is labeled with the emotion identified in the classification stage.

Unsupervised classification of facial emotions relies on clustering methods such as k-means cluster analysis, whereby the user inputs the number of clusters (i.e., the number of target emotions) and chooses a clustering method, but the algorithm groups video segments with the most similar facial attributes and then the user labels each group with the emotion that best characterizes the facial expressions in the group.

That humans use facial expressions to infer information about the emotional states of others is undoubted. When humans perform emotion inference from faces, they rely on their own emotion concepts as well on information they find in inspecting facial configurations, and the context within which the facial expression appears provides important additional information for the inference process. Computational approaches to recognizing emotions from facial expressions face some challenges. First, because emotion concepts can vary between cultures, some emotions might be missing or differently implemented in computational methods. Second, computers only have the concepts that humans give them, for example, through training sets or cluster labels. Human emotion categories have considerable heterogeneity within them—happiness does not always look the same—meaning that computational methods may not always accurately recognize the emotion a person expressed in a facial expression. Finally, computational methods are often agnostic to the context in which the facial expression appeared and may thus misclassify which emotion is being expressed in the facial configuration.

Sentiment Analysis of Linguistic Responses

Emotions in Text

In addition to bodily responses such as facial expressions, emotions are expressed using language. While nonverbal cues like facial expressions can provide some information about the emotion a person is experiencing, language makes it possible to express the richness of emotions and thus gives more precise information about the specific form of an emotion that is experienced.

Emotions can be detected in written language because individual words can have emotional content. This phenomenon is called affective connotation and can be described as the aura of feelings that surrounds virtually all words. In turn, this means that affective connotation can be also defined as the emotional reaction that is triggered in a person by using or reading/hearing a given word.

Sentiment analysis is the research area studying the relationship between written language and emotional information and dealing with its computational processing. It focuses on text, which is an important medium for extracting emotions because many human–computer interfaces are still based on text.

Sentiment analysis originates from text mining and computer linguistics and deals less with the content analysis of written language but rather with the sentiment, emotions, attitudes, opinions, and evaluations contained within it. Often sentiment is conceived in the sense of positive, negative, and neutral, but a significantly larger number of potential emotions, such as joy, sadness, hate, excitement, fear, etc. can also be considered. Sentiment analysis is sometimes also called opinion mining, sentiment extraction, or sentiment detection.

Classification Methods

Sentiment analysis can be undertaken using machine learning approaches or lexicon-based approaches. As in emotion recognition from facial expressions, machine learning approaches can be either (semi-) supervised or unsupervised, among others. Machine learning techniques aim to classify a text into predefined categories by making use of linguistic and/or syntactic features. In contrast to unsupervised learning methods, supervised machine learning methods require labeled training documents. Another form of machine learning used for sentiment analysis is deep learning, which is based on neural networks.

Lexicon-based approaches can be differentiated into dictionary-based and corpus-based approaches. Both make use of lists containing opinion words that are used in written language in order to express desired or undesired states. In the case of dictionary-based approaches, each word in a text is looked up in the opinion word list. That has the disadvantage that context-specific orientations of opinion words cannot be identified. Corpus-based approaches attempt to find the orientation of opinion words while considering the specific context in which they appear with the help of syntactic patterns.

Despite diverse classification methods, sentiment analysis is not always accurate—written language can be interpreted differently by computers and humans. Jokes, sarcasm, irony, slang, or negations are typically understood correctly by humans, but can cause errors in computational analysis. Moreover, texts can be difficult for computers to assess due to missing information regarding the context the text was written in or refers to.

Sentiment Analysis From Location-Based Social Media

Sentiment analysis has attracted attention as a method for understanding emotional responses to people, events, and places with the increasing availability of location-based social media (LBSM). Recommendations, ratings, reviews, and expressions of opinions provide a new data source for those in business, politics, science, government, and other fields. This kind of data can have an implicit (in the form of toponyms) or an explicit (geographic coordinate or a geotag) spatial reference. In addition to images, video, or audio, most social media content includes text to which sentiment analysis can be applied. Examples are microblog contents with a coordinate (e.g., on Twitter), georeferenced photos with textual metadata like titles, descriptions, and tags (e.g., on Flickr), or location-based recommendations (e.g., on Foursquare). Georeferenced photos from platforms like Flickr capture and depict places. Thus the respective metadata (e.g., descriptions) are highly likely to refer to these places and may convey the user's feelings related to them. On the other hand, with geo-located micro-blogging content like tweets, the user may be tweeting about an incident located somewhere else.

LBSM content has usually a short text length. The advantage of this feature is that the contained sentiment is typically rather explicit and compact, and noise can be filtered out effectively, which makes sentiment classification easier. A longer text does not necessarily mean that the amount of sentiment contained increases proportionately.

Sentiment analysis can be applied to LBSM posts based on the assumption that users tag, describe, and title photos of a place differently when they liked a place than when they felt uncomfortable there. It not likely that users concretely name the specific emotions they felt at a particular place, but nevertheless their emotions and sentiments are reflected in their word choices. That means, for example, that the description of a scenic park that provoked positive emotions in a person, or of a decayed ruin that was perceived to be scary, is likely to contain words with respective affective connotations even though the user's emotional state is not explicitly stated in this description.

When considering recent research that applied sentiment analysis to LBSM content, common tendencies regarding the extracted sentiment, data sources utilized, classification methods applied, and underlying motivations of the study as well as visualizations used to show emotional responses become apparent. These trends are summarized below.

Twitter is the most frequently used data source when researchers apply sentiment analysis techniques to LBSM content. Foursquare, Flickr, and Panoramio are utilized much less frequently. Also, multiple sources are employed together only rarely. The reason for Twitter's popularity as a data source—despite the relatively low proportion of tweets that are geotagged—is unquestionably due to the fact that tweets are available in a large and steadily growing number and at a high spatiotemporal resolution.

The sentiment extracted from LBSM content is defined in several different ways: either as a polarity, as a dimensional structure, or as emotional categories. The vast majority of studies consider sentiment as polarity, mostly in the form of a positive-negative continuum. There are differences in how the positive-negative polarity is subdivided. Some studies use the categories positive and negative, and some also include neutral; others define it as a numerical scale, either real- or integer-valued. Besides positive-negative, sentiment polarity is occasionally also seen as a happiness scale. Dimensional structures are applied rarely, and the dimensions of valence and arousal are used in all cases that use dimensional approaches. If sentiment is described in the form of emotional categories, between five and eight categories are usually distinguished. The most frequently occurring categories are happiness, anger, fear, sadness, and surprise, which appear in many approaches as "basic emotions." The fact that sentiment is mainly extracted as a positive-negative continuum from LBSM content, that is, in a rather elementary form, reflects the difficulty of identifying more specific emotions due to ambiguity in the interpretation of the emotional content of text.

Both machine learning approaches and lexicon-based approaches are frequently used for sentiment classification. Within the lexicon-based approaches, dictionary-based approaches are used more frequently than corpus-based ones, probably due to the more straightforward nature of their usage. (Semi-) supervised learning is the most frequently chosen method among machine learning approaches. Different approaches are combined only rarely.

The motivations for conducting sentiment analysis using LBSM content range from very general to quite specific. A general motivation means that the aim was to generally test or introduce an approach for sentiment analysis of LBSM content; however, other studies have rather specific aims, like supporting urban planning, monitoring environmental changes, analysis of spatial patterns of crime, or mental health research. For example, tweets with negative sentiment that are linked to particular locations can be used to identify urban problems like places where people feel uneasy walking at night, unexpected traffic jams, or damaged infrastructure. In another example, researchers attempted to monitor mental health problems through the analysis of emotions expressed in tweets following a terrorist attack in Paris. The fact that there are both general and specific motivations for conducting sentiment analysis underlines the fact that on the one hand sentiment analysis is still under development, but on the other hand, broad fields of application nevertheless arise.

Visualizing Emotions in Maps

Typically sentiments extracted from LBSM content are stored as point objects, that is, as an emotion with a geographic coordinate, but in some cases these points are aggregated to areas. Thus maps visualizing sentiment in space employ either point- or area-related visualization methods. Nevertheless, not all applications contain a map despite dealing with spatial data. The most frequently used visualization is an isoline method: a heat map representing the density of sentiments; followed by point symbols that are often distinguished by using different color hue for positive and negative emotions. Choropleth maps and point diagrams are other commonly applied representations. Because emotions often change over time, many maps of emotions and sentiment provide the capability to filter emotion and sentiment information for different time periods and/or depict this information in real- or near-real-time

When sentiment is modeled as a dimensional structure, its presentation in a map becomes challenging as this requires multivariate visualization because in addition to geographic latitude and longitude, the emotional dimensions like valence and arousal need to be considered for a point object. This problem can be solved, for instance, with a two-dimensional color legend based on a scale from light to dark for arousal combined with a scale from red over yellow to green ("traffic light principle") for valence (see

Fig. 3A). In Fig. 3B this color scheme is used for choropleth mapping with hexbins as reference units, and all emotional values within one hexbin are averaged.

Another option is to uncouple spatial emotional information from the map by multi-windowing, as implemented in the *We Feel* web application. *We Feel* is an application designed to explore how emotions fluctuate over time and space. To do this, the

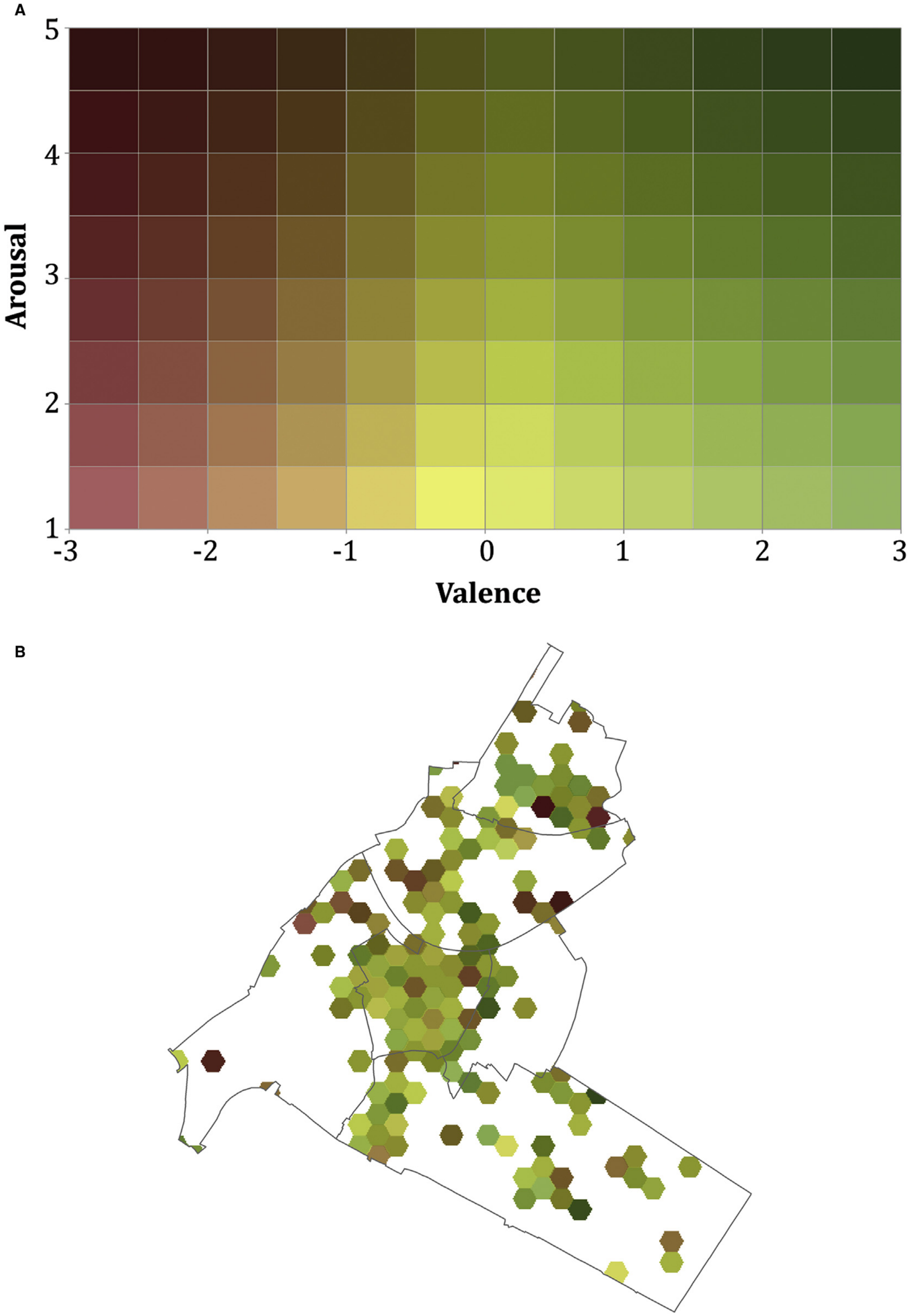

Figure 3 (A) Legend for valence and arousal applying two color scales, (B) Choropleth map of emotions in the inner city of Dresden (Germany) extracted from the metadata of georeferenced Flickr and Panoramio photos.

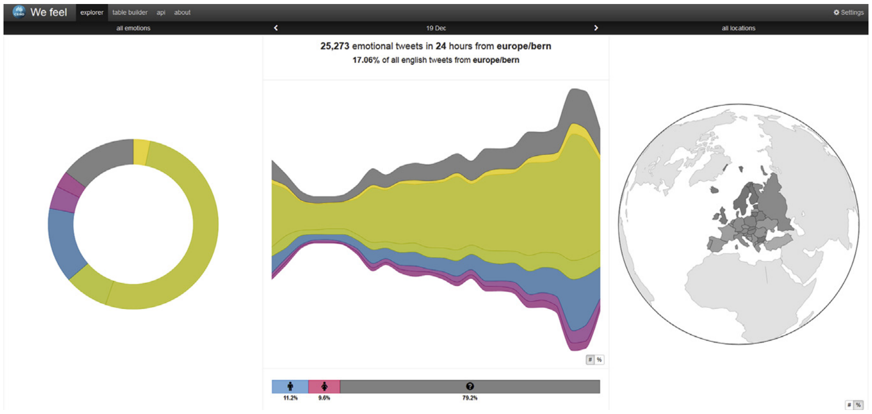

Figure 4 *We Feel* web application showing emotional categories extracted from tweets for a selected country and day. Screenshot of http://wefeel.csiro.au, © Copyright CSIRO Australia.

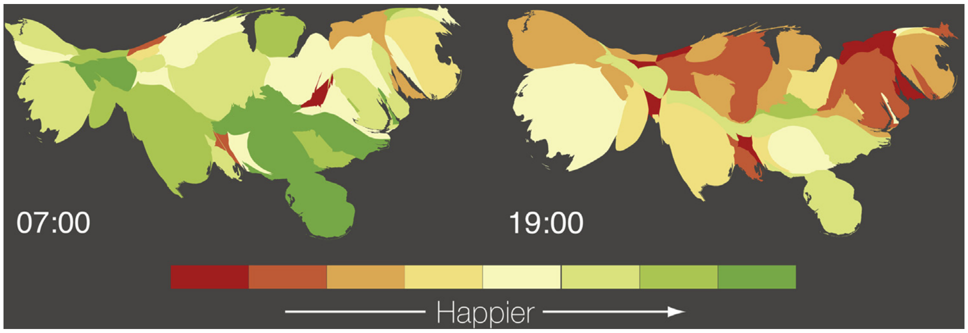

Figure 5 Average happiness in the United States at 7 a.m. and 7 p.m. Adapted from https://mislove.org/twittermood/ (shared under the Creative Commons Attribution 3.0 License).

application performs sentiment analysis on tweets obtained from Twitter's public API. *We Feel* offers a map, but its map is merely used to select an area of interest from 83 countries. Outside the map, the related emotional data (comprising seven categories: surprise, joy, anger, sadness, fear, love, other) are shown as a circular ring diagram for the selected area and day and as a theme river covering each hour of this particular day (see Fig. 4). Additionally the data can be filtered by gender and emotion.

Real-time mapping of sentiment has many potential applications including for disaster response. Situational awareness is often challenging in disaster situations because the situation can change rapidly. Sentiment analysis applied to geocoded tweets can provide additional information about an affected population's emotional experiences and their relative distances to the disaster, indicating where people may need help or where they are doing well.

Informative visualizations can be also achieved by using cartograms. In Fig. 5 the choropleth symbolization represents the happiness per US state, whereas the size of each state varies depending on the number of tweets. In this case, the variation in happiness in the United States extracted from tweets at 7 a.m. and 7 p.m. is illustrated.

See Also: Affect; Behavioral Geography; Emotional Geographies; Memory; Place; Sense of Place.

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