한국지리학회지 5권 2호 2016(213~223)

A Theoretic Review of Emotional Language Analysis on Twitter Microblog and the Geography of Emotion

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트위터 마이크로블로그의 감정 언어 분석과 감정 지리학에 대한 이론적 고찰

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요약 : 사회네트워크서비스(SNS)는 다양한 연구 분야의 중요한 데이터 소스로 점차 각광받고 있다. 특히, 트위터와 같은 마이크로블로그에 대한 어휘 분석은 마이크로블로그가 탑재하고 있는 내용 뿐 아니라 지리 정보나 인적 네트워크와 같은 비어휘적 정보를 풍부하게 제공할 수 있기 때문에 매우 중요한 데이터 소스로 인식되고 있다. 본 연구는 다양한 어휘 분석적 접근 중에서 감정 언어와 감정 지리학에 초점을 맞춘 마이크로블로그 분석의 최신 이슈들을 이론적으로 고찰하고자 한다. 이를 위해 본 연구는 감정 및 지리학에 관련된 세 가지 주요 연구 분야의 발전을 살펴본다. 먼저, 지리학과 컴퓨테이션 분야의 연구에 영향을 끼치고 있는 현대 심리학의 감정 분석에 대한 이론적 프레임워크를 살펴보고, 마이크로블로그의 감정 언어 분석과 감정 분류에 대한 주요 이슈와 컴퓨테이션 발전을 논의한다. 다음으로 감정 지리학과 관련한 마이크로블로그 분석 방법을 트위터를 중심으로 살펴본다. 마지막으로 마이크로블로그 분석과 관련하여 향후 보완되어야 할 연구 주제와 지리적 연구 목적을 위한 컴퓨테이션 방법의 개선에 대해 논의한다.
주요어 : 감정 언어, 감정 지리학, 감정 분류, 마이크로블로그, SNS, 트위터

Abstract : Social networking services (SNS) have become an increasingly important source of data for various fields of research. In particular, lexical analysis of microblogs such as Twitter have become important sources of data both because of the content of the microblog itself and the metadata that provides a wealth of alternative non-lexical information about a tweet such as geographic location and network of acquaintances. Among various lexical approaches, this paper attempts to theoretically review the cutting edge issues of microblog analysis, particularly focusing on emotional language and the geography of emotion. For doing this, this paper explores the evolution of three distinct fields of research in relation to emotion and geography. First, we discuss the theoretical framework of emotional analysis in modern psychology which might affect research in both geographic and computational fields. Next, major issues and computational advancements into emotional language analysis on microblogs are discussed. And then, microblog analysis in relation to emotional geography is generally discussed focused on Twitter. Lastly, what should be conducted for future research and how computational methods can be improved for geographic research purposes are discussed.
Key Words : Emotional language, Geography of emotion, Emotion classification, Microblog, SNS, Twitter

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I. Introduction

Social networking services (SNS), such as Twitter have had an ever increasing role in academic research due to the availability of large amounts of data. This is because Twitter and other microblogs allow users to express their thoughts while connecting with others. Twitter in particular, as the most widely used microblogging service, has been mined and extensively investigated by researchers to help determine public opinion in an array of fields including predicting stock markets (Bollen *et al.*, 2011) and elections (Tumasjan, 2010), studying the spread of disease (Wang *et al.*, 2016; Do *et al.*, 2016), and to helping during crisis situations (Kwon and Kang, 2016; Laylavi *et al.*, 2016) among others.

This paper attempts to theoretically review the cutting edge issues of microblog analysis that has particularly paid attention to emotional language and the geography of emotion. Emotions have become a major issue for human geographic research since the humanistic geographies of the 1970s and 1980s, and a broad spectrum of topics in emotional geography has been expanding (Pile, 2009). Emotional geography deals with the relationship between human feelings and geographic places which is one of interesting topics in humanistic geography. Recently developments of blogs or microblogs open up new opportunity in exploring human emotions of locations because people wish to share their activities and locations with others through the microblogs (Gallegos *et al.*, 2015). Research conducted in this field is of particular importance because microblogs "provide a medium for finding the spontaneous feelings and opinions that people express voluntarily…" (Chakraverty, 2015). Furthermore, the microblogger has a perceived audience through which they present themselves, leading to a more honest representation of the user's feelings (Marwick and Boyd, 2010). This has led to the explosion in popularity of SNS sites like Twitter, which is one of the internet's most visited sites at 310 million monthly active users (Twitter, 2016). The large amount of spontaneous emotional data paired with geographic information provides researchers with a unique opportunity to study SNS users from a broad variety of perspectives. This can include analysis for disease, disaster, economic trends, political movements, targeted marketing, and city management among others. This is because microbloggers often express their emotions related to particular places or residential areas through their communication windows. This emotional language can plot the geography of emotional variation of places, and thus help us understand realistic sense of places and collect individual data in an efficient way. In general, it is quite difficult and costly to gather people's feelings for places in geographic research because it requires the direct or indirect survey of individuals.

In this context, this paper will evaluate three distinct academic fields that must be reviewed simultaneously in order to be a benefit to the geographic community. This paper will discuss modern research into what emotions are in the field of psychology, and what the accepted research on emotions is that might affect research pertaining to computational geography. Second, major issues and advances of emotion analysis in computational geography will be discussed. As this is the newest of the three academic fields this paper can help set a baseline for what should be accepted in computational research pertaining to emotion in geography. Next, microblog analysis in relation to geography will be generally discussed focused on Twitter. How data points are being gathered from microblogs and what how they are being used will be discussed. Last, future research opportunities in research methods and how to improve computational methods for geographic purposes will be discussed.

2. The theoretical framework of emotional analysis

Before discussing the relationship that emotion has with geography and computational fields the current research on what emotion is must be discussed. One of the preeminent scholars in emotional classification

Paul Ekman published research proposing seven distinct categories of emotions; happiness, surprise, fear, sadness, anger, disgust/contempt, and interest (Ekman *et al.*, 1972). Ekman's work became the basis for modern emotional categorization because it combined the past century of research into more easily understood and broader categories with more specific sub-categories of emotions. Later in his career Ekman published another paper that revised his ideas. He discusses the presence of nine characteristics of all emotions and the current research pertaining to his framework. He groups all emotions into emotion families that each shares nine distinct characteristics. From this paper he posited that there were six distinct emotion families that shared all of his nine characteristics (anger, fear, sadness, enjoyment, disgust, and surprise) and five other emotions that almost fit his framework (contempt, shame, guilt, embarrassment, and awe), but should be studied more extensively (Ekman, 1992).

Ekman's emotion framework has become much of the basis for emotional analysis of language in both geographic and computational fields in recent years. However, not all researchers have come to embrace Ekman's ideas. In particular, researchers in computational fields have been ignoring Ekman's contributions to emotional analysis, likely because of lack of resources, lack of computational power, or difficulty of analysis. However, with newer methods of analysis, these are quickly becoming poor excuses for ignoring preeminent research on emotion when analyzing emotion.

3. Emotional language analysis in computation

3.1 Detection and classification of emotions

When computational text classification was an emerging field, it focused on large blocks of text such as movie reviews (Chaovalit and Zhou, 2005; Turney, 2002), songs, blogs, and speeches (Dodds and Danforth, 2009; Neviarouskaya *et al.*, 2009; Alm *et al.*, 2005), and how to classify the text. However, many of these early papers also set a precedent in emotional text classification that was out of line with prior research conducted in psychology (Ekman, 1992) and the foundations of researching emotion in computing (Picard, 1997). Picard had in fact embraced the study of emotion in computing, or what she called "affective computing" saying that advances in affective computing "can help advance emotion and cognition theory." Although Picard seemed to agree with Ekman, technology and resources were not readily available when she published her work. A few years later, Liu *et al.* (2003) tried to classify separate emotions, but relied on a very small sample size that did not prove their results. Likely due to computing power, cost of research, and difficulty associated with multiple classes of emotions most researchers started using binary (positive vs. negative) emotion classification for text classification research. This, however, was out of step with Ekman's work and didn't follow current research in emotion and psychology, as he had long before noted that a pleasant-unpleasant scale is insufficient to distinguish between emotions (Ekman, 1992).

Despite psychologists claiming that binary classification was not enough to determine emotion, researchers continued using positive vs. negative dichotomies to analyze texts (Bollen *et al.*, 2011; Wang *et al.*, 2011; Hu *et al.*, 2013). Go *et al.* (2009) had mentioned that expanding the negative vs. positive dichotomy to include neutral text was a good idea, but it was not included in their research. Other research projects took this idea and expanded from a binary concept to include neutral emotion in their text classification (Pak and Paroubek, 2010; Kouloumpis *et al.*, 2011; Gonçalves *et al.*, 2013). While others, instead of using a classification system based on separate but distinct categories, created scales based on happiness (Mitchell *et al.*, 2013; Frank *et al.*, 2013; Bertrand *et al.*, 2013). Bertrand *et al.* (2013) went further with their research of New York City and mapped geotagged tweets. Their sentiment classifier determined that people were more likely to be positive closer to parks and tourist areas and more negative closer to transportation hubs. It produced interesting, but inconclusive results that couldn't explain what was negative and what was positive about certain areas. Furthermore, the researchers noted that although some cemeteries produced strong sentiments they couldn't explain why some were associated with positive and some with negative emotions. Nakov *et al.* (2016) claimed that their method of replacing a two or three point scale with a five point scale including both 'Highly Negative' and 'Highly Positive' was a good way to evaluate how consumers rate a product so it should also be a good way to determine sentiment of a tweet.

All of the methods using a dichotomous or similar scale system ignore research by psychologists in favor of simplicity. Later, as researchers started improving classification techniques and adding multiple classes of emotions, the technology had improved and could then follow current research in psychology, but continued to ignore it. This is a major failure on the part of text classification research that is only recently starting to become rectified.

In dichotomous or scale based classification the feelings of anger, fear, sadness, disgust, and perhaps even surprise would be considered negative by an algorithm, but a human could more easily understand and distinguish the differences between these feelings. These differences, although subtle, could even mean the difference between life and death. Luyckx *et al.* (2012) studied ways of detecting emotion in suicide notes that divided both between different sections of a note and different emotions in the note. Furthermore, with some calibration could prove useful in classifying and identifying potential suicide victims on social media. Luyckx *et al.* (2012) also notes that emotions cannot involve classifying documents as either negative or positive, because the differences in emotions are too subtle. Subtlety in emotional analysis proved to be a problem for Bertrand *et al.* (2013) in their study because anomalous results could not be explained, whereas if a more fine-grained approach to emotional analysis had been conducted it may have produced more interesting and useful results.

In more recent years a trend has been growing that breaks away from the positive to negative scale. This movement toward multiple emotional classifications seeks to rectify past mistakes in emotional classification research. Liu *et al.* (2003) was the first to attempt to lexically identify and label emotions in short text. In this paper the researchers created a prototype email application that was able to detect emotion in short bursts of text sent through email and attach a graphical representation of each of the six emotions outlined by Ekman (1992). Their research was able to point out the problems limiting the real-world approach to emotion classification in text, but with their small sample size weren't able to affectively solve any of those problems. Alm *et al.* (2005) later conducted research into emotional classification of children's fairy tales. Their research first divided between neutral and emotional text and then divided the remaining emotional text into seven separate categories. These included all of Ekman's six emotions, but divided surprised into "positively surprised" and "negatively surprised." While their research was able to define likely emotions in the text of fairy tales, it's difficult to know if their approach would work for classifying shorter text such as that in microblogs. Furthermore, fairy tales contain older and more established language that would likely be ineffective at evaluating newer shortened bursts of text and internet slang used on microblogs. Neviarouskaya *et al.* (2009) countered this problem by both evaluating fairy tales and the more free informal style of language used on blogs. They also took into account emotions outlined by Izard (1971), which included nine different classes of emotions. They noted that although their approach showed promise their dependence on a lexicon, as well as software limitations put critical restraints on their research that needed to be addressed.

Aman and Szpakowicz (2007) also encountered similar problems in emotional text classification while creating a corpus based on blog posts.

3.2 New approaches on emotional classification

Researchers have started focusing on moving past methods of classification and have started concentrating on novel ways to improve semantic detection from text. Luyckx *et al*. (2012) provided a way to detect the emotions, sentence by sentence, of text in suicide notes. Their research employed the use of prior research in classifying entire sentences like that of Liu *et al*. (2003) and showed a way to detect and possibly intervene if suicidal patterns emerge on social media. Tumasjin *et al*. (2010) used tweets to determine if tweets mirrored political sentiment and could accurately predict German and US elections. Although this approach provided interesting results, it also had many major problems. The first was that as Gayo-Avello (2012b: 1; 2012b: 2) has discussed the method of collection and results were flawed because they didn't take into account a number of factors and offered recommendations for researchers using Twitter data especially in relation to political data (Gayo-Avello, 2012b: 2). The other problem with the research Tumasjin *et al*. (2010) conducted was that it included a mixed bag of topics that overlap in scope or have no relation to each other. For example, they touched on both positive and negative emotions, but then also included sadness, anxiety, anger, tentativeness, and certainty as emotional classes. However, this was not conducted on a hierarchal structure which led to the data being skewed toward either positive or negative emotions. There were also other non-emotion subjects directly compared to the emotions topics that cannot be accurately compared in exclusivity. For example, work, money, and past- and future-oriented were all compared to emotions without acknowledging that these topics may be interrelated.

Possibly due to the explosion of data and the interest in classifying emotions in novel new ways, some researchers have employed the use of hierarchal classifications techniques in emotional classification (Ghazi *et al*., 2010; Xu *et al*., 2015). This new approach first divides between neutral, positive, and negative emotions, then further divides the emotion categories into more fine-grained categories. Other research in the same field in fact skip this step altogether, and divide text into six or more distinct categories usually defined by Ekman's six emotions (Bann, 2012; Kim *et al*., 2012; Li and Xu, 2014; Abdullah, 2015; Do and Choi, 2015; Do *et al*., 2016). Hierarchal structures might prove of some use as they could provide even finer grain emotional categories like those discussed by Ekman (1992). Similarly, Quercia *et al*. (2015) collected social media posts containing words from ten different smell categories before further breaking them down into finer grain smells, although their focus was not on emotion.

Li and Xu (2014) created a method of looking at Chinese microblogging site Weibo in which emotions were classified using emotion cause extraction. They did this by extracting cause event data and comparing the event to the emotion in the Weibo message. This is similar to the approach that Do *et al*. (2016) took when analyzing the emotions of tweets during the Middle East Respiratory Syndrome (MERS) outbreak in 2015 in South Korea. In this study they collected Korean language tweets related to the MERS outbreak and evaluated how public opinion surrounding the crisis related to the emotions of Twitter users. Both approaches were interesting variations of Hughes and Palen (2009) who describe the usefulness of tweets across high-profile, mass coverage events or what Li and Xu (2014) call 'emotion causes.'

The method that many researchers have used for collecting tweets is also open to bias results. The majority of studies on emotion in a tweet have used Twitter's Application Program Interface (API) to collect tweets. There are two methods a researcher can take to collect tweets using Twitter's API. The first method, and the most commonly used, is searching for tweets by keyword or phrase. The second method is to use Twitter's streaming API service to pull tweets off of the microblogging site that are being posted in real-time. The first approach has proven to be useful for emergency events (Hughes and Palen, 2009; Kwon and Kang, 2016; Laylavi *et al.*, 2016), or evaluating specific topics (Wang *et al.*, 2016; Do *et al.*, 2016; Bollen *et al.*, 2011). However, it is not very helpful in evaluating emotion over an entire population or in building a corpus due to the inherent bias that certain feeling words or keywords will have. One of the largest corpuses designed to classify tweets was designed by Go *et al.* (2009) using emoticons common in English language tweets at the time of publishing. These emoticons included happy emoticons such as ':-)' and ':)' as well as sad emoticons such as ':(' and ':-('. Their process scraped twitter for tweets with these specific emoticons to be used as classifiers for building an English language emotion corpus. This method of collection would have to be modified for non-English languages or more current tweet language. Furthermore it biases emotional labeling towards users who use very specific course emotions, possibly only benefiting positive and negative emotion classifiers or even happy vs. sad. Do and Choi (2015) were able to construct a more accurate twitter based lexicon by randomly scraping tweets in the Korean language. They first removed tweets with retweets, URL links, and replies before manually annotating tweets with seven emotion labels. They were able to train their machine learning algorithm to construct an emotion lexicon for the Korean language.

4. Twitter microblog analysis

When mining tweets using the Twitter API a plethora of information is given that helps us study the behaviors of people. A setting in the API lets a researcher narrow down results by geographic coordinates. However, this only works with geotagged tweets and for a tweet to become geotagged a Twitter user must opt in to the service. This has created a problem for researchers as location information is critical to applying data from the internet to the physical world. Cheng *et al.* (2010) noted that Twitter users have been slow in opting in for this service with only 26% of users listing their location at a city level and others are overly broad or even nonsensical, as this is volunteered by the user. In their study they found that less than 0.42% of all tweets in 2010 used the geotagging feature. A few years later Weidmann and Swift (2013) found that while users who had enabled the geotagging feature had increased, it was still a small number. They found that "On average about 3.5 percent of tweets were location enabled" and "Additionally, 2.2 percent of all tweets… were providing substantial ambient location data in the text of their tweets."

By creating a content-based location estimation model Cheng *et al.* (2010) were able to narrow down 51% of Twitter users to within 100 miles (161 km) of their location. Since then, a number of other researchers have used a variety of methods to improve location identification location of a non-geotagged tweet or a tweet with non-specific or generic coordinates. This has been done by two main methods in research: lexical or network based.

Lexical-based geotagging has mostly been conducted by identifying and searching for location specific terms using Twitter's streaming API (Cheng *et al.*, 2010). More recently new algorithms have been developed to determine at different granularities the location of a Twitter user (Mahmud *et al.*, 2012; Mahmud *et al.*, 2014). The more recent work was able to predict a user's location from 61%~80% depending on granularity. This, however, is an approach that depends on the uniformity of language or the accuracy and inclusion of regional dialects and languages and likely could not be replicated in non-English speaking regions. Other lexical approaches such as one based on dialectical differences also would not help in increasing accuracy as a globalized world and traveling users could skew results (Compton *et al.*, 2014).

Network based geotagging of tweets is much more common. It is made possible through inferring a Twitter user's location through the locations of their friends. This approach is based on the communicative locality of Twitter users. In other words, your contacts on social networking platforms like Twitter are likely to live near you. In the research by Takhteyev *et al.* (2011) and Jurgens (2013) both relied on the assumption that a twitter user was correctly identifying a geographic location that they were actually located in, which has been criticized by Johnson *et al.* (2016). Both research papers left out obvious fantastical and overly broad self-reported locations from their studies, but failed to analyze how accurate the remaining self-reported results actually were. Takhteyev *et al.* (2011) who set the basis for this research concluded that, "Ties at distances of up to 1000 km are more frequent [on social networks] than what we would expect if the ties were randomly forme d…" This distance is so large that in reality it is only able to identify centers of large Twitter users like New York, Los Angeles, Sao Paulo, and Tokyo, and shows more of a correlation between languages of likely followers than location. Johnson *et al.* (2016) criticized this approach too claiming that the assumption of localness "does not hold for approximately 25% of social media [Volunteered Graphic Information]."

Despite the relative unreliability of volunteered information researchers have continued to hold to the localness assumption. Compton *et al.* (2014) in particular ignored the inaccuracy of volunteered information relying on the assumption that it was accurate developed a method to geotagging a large number of tweets. Chandra *et al.* (2011) sought to avoid using purely self reported location information and instead developed a content based approach using only known locations of Twitter users, or those who had opted into the geotagging service on a mobile device, to identify the geographic locations of related Twitter users. Davis *et al.* (2011) also sought to identify Twitter user location using social interactions, but instead by recursively expanding the network of locatable users. Both sets of researchers decided that although their methods improved the accuracy of estimating a user location more research was needed with larger data sets. Davis *et al.* also concluded that users with too few or users with too many followers skewed results and could not reliably predict locations of other users related to them. Kotzias *et al.* (2015) operated under the premise that volunteered information, although useful, is likely flawed. They specifically concentrated on relationships between users who communicated on a regular basis. Comparing geotagged users with their non-geotagged relations gave researchers the ability to extract the likely geolocation of a user to within blocks all while acknowledging the imperfectness of volunteered information and stepping around problems with the localness assumption. Unfortunately, this method used only a small subset of users from three cities, so it should be more thoroughly explored in the future. Rodrigues *et al.* (2016) explored similar problems in location analysis by examining the text of the tweets as well as user networks and found that relatively few users' locations need be known to infer the location of others.

In non-computational fields of research location of Twitter users has also been important. It has mostly been conducted using topically centered data such as a disease (Broniatowski *et al.*, 2013; Wang *et al.*, 2016; Do *et al.*, 2016), flood (Kwon and Young, 2016), natural disaster (Laylavi *et al.*, 2016), or even sentiment (Bertrand *et al.*, 2013; Chakraverty *et al.*, 2015). In these studies average user location was less important than tweet location. This is because the location of a tweet is more critical to each of these studies. In research on disease Wang *et al.* (2016) and Broniatowski *et al.* (2013) rely on self-reported locations in Twitter in order to find the location of the tweet. However recent research indicates that this method is flawed as self reported locations should not be used for research due to inaccuracy (Johnson *et al.*, 2016). Do *et al.* (2016) simply analyzed emotions in the tweets, and did not implement location analysis. Kwon and Young used POI data for Seoul, South Korea to extract exact tweet location. This method is the most promising for data on the micro scale as it is able to pinpoint exact coordinates within a specified area. Unfortunately, the downside to this method is that POI (Points of Interest) information is often costly and time consuming to produce for research. Laylavi *et al.* (2016) used self-generated POI data from freely available Australian GIS shapefiles combined with tweet content to infer the location of 87% of the tweets they sampled to an average distance of 12.2km. Laylavi's method shows promise for low budget areas, and although not exact, helps to improve prior methods of identifying tweet location. Chakraverty *et al.* (2015) extracted tweets within the borders of three separate cities, but did not attempt to narrow down the location further instead concentrating on emotional analysis of the tweets. Bertrand *et al.* (2013) used the coordinates attached to a tweet by twitter users who had opted into geolocation services. However, they did not attempt to narrow down the results to the micro level instead opting to evaluate emotions by neighborhood in New York City. They obtained interesting results showing negative emotions near roadways and graveyards, and positive emotions near parks. Unfortunately, the decision to evaluate points at the macro level may have contributed to anomalous results where some positive emotions occurred near one graveyard, and the researchers could only make guesses as to why they had obtained their results. More fine-grained emotional analysis or more fine-grained location analysis may have led to more revealing results.

5. Concluding remarks

Microblog like Twitter is a treasure-trove of information for researchers. However, methods for classifying location and topical information at finer grains still need to be refined. Emotional analysis of tweets at a finer grain seems to finally be coming to a consensus that Ekman's emotional categories and a neutral category are needed for a fuller analysis of tweets. Furthermore, most current research seems to have decided that a positive-negative dichotomy even on a scale is insufficient to capture the complexity of human emotions. Location analysis of on Twitter offers several different roads that still have to be explored. If the location of the Twitter user is more beneficial to the researcher for mobility pattern analysis, election analysis, advertising, etc. then the most popular current approach seems to be in using the location of acquaintances on social networks to determine location of the user. This method may be especially beneficial in the future combined with textual analysis of location and emotion for targeted advertising in particular. If the location of the tweet is more important to a researcher's purpose such as in studies pertaining to disease, flood, disaster, and sentiment, then textual analysis combined with POI data seems to be the best for determining exact or close to exact location.

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투 고 일: 2016년 7월 22일
심사완료일: 2016년 8월 10일
투고확정일: 2016년 8월 11일