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Social Media Data as a Source for Studying People's Perception and Knowledge of Environments[1)]

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with 3 Fig. in the text

Contents

Zusammenfassung

Soziale Netzwerke als Datenquelle zur Untersuchung von Raumwahrnehmung und Raumwissen

Die steigende Verfügbarkeit von sozialen Netzwerken und Sharing Services im Internet (z.B. Facebook, Foursquare und Flickr) hat zu einer großen Menge an Mediendaten geführt. Diese Daten enthalten, besonders wenn sie mit einer Geokodierung versehen sind, viele Informationen über die Erfahrungen und Aktivitäten der Nutzer hinsichtlich ihrer Umwelt. Dieser Artikel präsentiert drei Fallstudien, die das Potenzial dieser Daten zum besseren Verständnis der Raumwahrnehmung und des Raumwissens von Menschen aufzeigen. Diese Fallstudien zeigen, dass Daten aus sozialen Netzwerken

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eine nützliche Quelle für Untersuchungen der Wahrnehmung und Konzeptualisierung der Umwelt sind. Abschließend werden einige soziale und technologische Herausforderungen in der Analyse von derartigen Daten diskutiert, die einer weiteren Untersuchung bedürfen, z.B. die „digitale Kluft", Datenqualität und Datenschutz.

Summary

Recently, the increasing availability of online social network and media-sharing services (e.g. Facebook, Foursquare and Flickr) has led to the accumulation of large volumes of social media data. These data, especially geotagged ones, contain lots of information about people's perception of and experiences in various environments. This article presents three case studies to illustrate the potential of these data for understanding people's perception and knowledge of environments, especially urban environments. Results of the case studies show that social media data are a useful source for studying how people perceive, conceptualise, and feel about environments. Finally, this article discusses some socio-technical challenges that need further investigations when analysing social media data, such as the "digital divide", data quality, and privacy.

1 Introduction

In the last several years, with the rapid spread of Web 2.0, more and more people have started to use online social networking services in their daily life. These social networking services, such as Twitter (*http://www.twitter.com/*), Foursquare (*http://www.foursquare.com/*), and Flickr (*http://www.flickr.com/*), allow people to create, share, and exchange information and ideas on the Internet. These User-Generated Contents (UGCs) can be text-based messages, check-ins, reviews/ratings, images, videos, and so on. Due to the success of these social networking services, huge amounts of UGCs are being created every hour, or even every second. Many of these UGC data are tagged with geographic location information, e.g. latitude/longitude.

The highly available UGCs or social media data have been opening up many new possibilities for research and applications. In recent years, analysing social media data has gained significant attention. Research on this aspect has focused on social network analysis (MCGLOHON et al. 2011), community detection (ZHOU et al. 2007), social influence analysis (ANAGNOSTOPOULOS et al. 2008), real-time event (e.g. disasters) detection (SAKAKI et al. 2011), place recommendations (DE CHOUDHURY et al. 2010; WAGA et al. 2012), behaviour analysis (JANKOWSKI et al. 2010; ZHENG et al. 2011), and so on.

Different from the above research, our research aims at using social media data for studying people's perception and knowledge of environments. This is promising, as more and more social media data are now tagged with geographic location information, and many of these geotagged data reflect how people perceive, experience, and behave in various environments. Analysing these data enables us to gain a better understanding of people's perception and knowledge of these environments, which is one of the key research aims in many disciplines, such as geography, environmental psychology, and computer science.

This article summarises our recent research efforts addressing these issues. We present three case studies to illustrate the potential of social media data for understanding people's perception and knowledge of environments, especially urban environments. In section 3, we address the socio-technical challenges of analysing these data, and biases to be considered when interpreting results. Finally, we draw the conclusions.

2 The potential of social media data for studying people's knowledge of environments

As acting in space, people perceive the environment and acquire knowledge to build mental representations of the external world. These mental representations (or mental maps) can be considered as our spatial knowledge about the environment. This knowledge is crucial in our daily life. It helps to organise our experiences, as well as to fulfil spatial tasks, such as orienting and wayfinding (Siegel & White 1975; Golledge 1999). All these are of vital importance to humans. Therefore, understanding people's perception and knowledge of environments is fundamental to many research disciplines, such as geography (e.g. human geography and GIScience) and environmental psychology. It also enables many applications such as location-based services (LBS), urban planning, and policy making.

Conventionally, research on this aspect often employs empirical experiments in labs or in fields (MacEachren 1991; Montello et al. 2003), which are often very expensive and time-consuming, and hard to apply for large-scale studies. Recently, with the impetus of social networking services, large volumes of social media data have been continually created. These data, especially geotagged ones, contain lots of information about people's experiences and activities in various environments, which might be a new and significant source for studying people's perception and knowledge of these environments. In the following, we present three case studies to illustrate the potential of these data for addressing this aspect.

2.1 Case study 1: Modelling the perceived boundaries of the Vienna [Wien] city centre

In daily life, people often use vague concepts like *city centre* and *area around train station* to conceptualise and communicate about space. Hollenstein & Purves (2010, p. 22) argued that "vagueness is inherent to the way humans conceive and refer to geographic locations". Existing research on this aspect often employs empirical experiments (Montello et al. 2003).

In recent years, the highly available social media data have enabled us to access information about how people use vague concepts in daily life. This information can be used to model humans' conceptualisation of space, e.g. modelling their perceived boundaries of the city centre. This case study illustrates how photos and their metadata (i.e. title, descriptions, tags, and location) on Flickr[2] can be used to study humans' perceived boundaries of the city centre in Vienna (Austria). A similar research was carried out by HOLLENSTEIN & PURVES (2010), who used Flickr photo tags to describe the borders of the city centre in many cities, such as Zurich [Zürich] and Chicago. However, their research did not differentiate the tags given by tourists and those by local residents, and therefore, it is still unclear whether the perceived boundaries of the city centre for local residents are the same as for tourists. This case study explicitly addresses this issue.

When uploading a photo to Flickr, users can add a title and some descriptions to it. They can also annotate the photo with tags, which are keywords and terms. These tags help to describe, organise, search, and share a photo. By looking at the Flickr website, one might find many photos having some terms like *city centre, downtown*, and *Innenstadt* in their titles, descriptions, or tags. The geographic locations of these photos (i.e. where these photos were taken) might reflect their users' implicit feedback and perception about where the city centre is located. Therefore, by aggregating the geographic locations of these photos, the perceived boundaries of the city centre can be modelled for the users who took the photos. In this case study, by carefully studying the terms used for describing city centre in both German and English (UK and US) languages, we use the list of *city centre, city center, downtown, inner city, Stadtzentrum, Innenstadt, Stadtmitte, Stadtinneres*, and *Stadtkern* for identifying these photos. More specifically, for each photo within the administrative boundary of Vienna, if one of these words appears in its title, descriptions, or tags, we consider this photo being taken in the city centre. In theory, it is possible to determine the city centre for each user if many photos from this user are available. However, this is not the case for most of the users. Therefore, instead of modelling each individual's city centre, we are interested in comparing the collective city centre for the group of local residents and that for tourists.

Due to the lack of home information in many users' profiles, it is impossible to identify a user as a local resident or a tourist according to this aspect. Therefore, we employ the heuristic rule proposed in DE CHOUDHURY et al. (2010) to differentiate tourists and local residents. The rule is based on the assumption that while most tourists concentrate their visits within a short time period of several days, local residents tend to take pictures of the city over a much longer period of time. Therefore, tourists and residents can be differentiated by checking the span of the taken times between their first and last photos. Similar to DE CHOUDHURY et al. (2010), we set the time span threshold as 21 days.

After photos of the Vienna city centre for local residents and tourists are identified, we then use Kernel Density Estimation (KDE) to derive the perceived boundaries of the Vienna city centre for local residents and for tourists. KDE calculates the density of features (i.e. photos in this research) in a neighbourhood around those features (SILVERMAN 1998). The density distribution can be then used to generate contours

[2] Flickr is a photo-sharing website, which allows users to upload and share photos on the Internet.

Source of the background maps: ESRI

Fig. 1: The perceived boundaries of the Vienna city centre for local residents (left) and for tourists (right). For both map views, 50%, 70%, and 90% contours of the volume surface are shown.

of the volume surface. In this research, we employ the KDE tool available in ESRI ArcGIS 10.1 to derive the perceived boundaries of the city centre. In order to have the results comparable, we use the same KDE parameter values for both local residents and tourists, which are set according to the default values auto-computed by ArcGIS 10.1. The results are then classified and converted to polygons using the "Reclassify" and "Raster to Polygon" tools available in ArcGIS 10.1.

Figure 1 shows the results, comparing local residents' perceived boundaries of the Vienna city centre and tourists'. These results are generated using the photos that were taken during January 2007 and January 2011, and tagged with locations within the administrative boundary of Vienna.

Figure 1 shows that both local residents and tourists perceive the area around Stephansdom, which is a landmark of Vienna, as the city centre. However, local residents' perceived boundaries of the Vienna city centre are very different from tourists'. Compared to tourists, local residents have greater consensus with each other in defining the boundaries of the city centre. This is consistent with the findings of BEGUIN & ROMERO (1996), which showed that differences in individual cognition decrease over time (or with increased familiarity).

Results of the case study show that social media data are a useful source for studying humans' conceptualisation of space, e.g. the perceived boundaries of the vague concept *city centre*. Compared to the conventional methods such as empirical experiments, analysing social media data enables us to investigate these issues with large-scale studies (e.g. with many participants). However, it is important to note that this case study employs a rather simple data analysis technique. In order to draw a clearer conclusion regarding the differences between local residents and tourists, more research should be done on the aspect, e.g. finding a better approach for differentiating locals and tourists, and analysing the user profiles to study the biases of these data. Section 3 has a more detailed discussion on this aspect.

2.2 Case study 2: Modelling people's affective responses towards environments

Humans perceive and evaluate environments affectively. Some places are experienced as unsafe, while some others as attractive and interesting. These affective responses to environments form our spatial knowledge about environments, and influence our daily behaviour and decision-making in space, e.g. choosing which places to visit.

Conventionally, people's affective responses towards environments are studied and collected through various approaches, such as self-reports in labs or in fields (Matei et al. 2001; Mody et al. 2009), and physiological recordings via sensors (Nold 2009). Recent research has also started to use social media data for studying people's affective responses in space (Mislove et al. 2010; Hauthal & Burghardt 2013). However, these approaches extracted people's affective responses **in** various environments, which might not necessarily be **caused by** or **towards** these environments. In this study, we extend existing research, and illustrate the potential of social media data in modelling people's affective responses towards environments.

Similar to the first case study, we also use metadata (title, descriptions, tags, and locations) attached to Flickr photos, which were taken during January 2007 and January 2011, for data analysis. We are aware that not all the Flickr photos are about the environment (e.g. many of the photos are portraits of humans), and people often include a place name (e.g. *Stephansdom*) or a place noun (e.g. *museum*) in the title, descriptions or tags of a photo when it is about the environment. Therefore, we only analyse the photos whose title, descriptions, or tags contain a place name or a place noun like *airport, museum*, etc. By this, we might be more likely to extract people's affective responses towards environments.[3] Sentiment analysis or opinion mining refers to the application of natural language processing (NLP) and text analytics to determine an author's attitude with respect to the topic written about (Wikipedia 2013). Therefore, sentiment analysis techniques are employed to process and analyse the title, descriptions, and tags of each photo. More specifically, for each photo, we use the Stanford CoreNLP 1.3.4 library to lemmatise its title, descriptions, and tags, and clean the sentences by removing English stop words (e.g. *a*, *by*, and *since*). Results of these steps are a list of words. For each word in this resulting list, we check whether it is in the AFINN list, which is an affective lexicon developed by Nielsen (2011) and has been applied by many other researchers.[4] If yes, we assign the valence

[3] Another possible approach is to analyse the visual features (content) of the photos by employing computer vision and image understanding techniques, and only use photos about places.

[4] AFINN contains a list of English words rated for valence with an integer between -5 (negative, unpleasant) and +5 (positive, pleasant). For example, in AFINN, "nice" is rated as +3, and "terrible" as -3. See *http://neuro.imm.dtu.dk/wiki/AFINN* for a list of studies using AFINN.

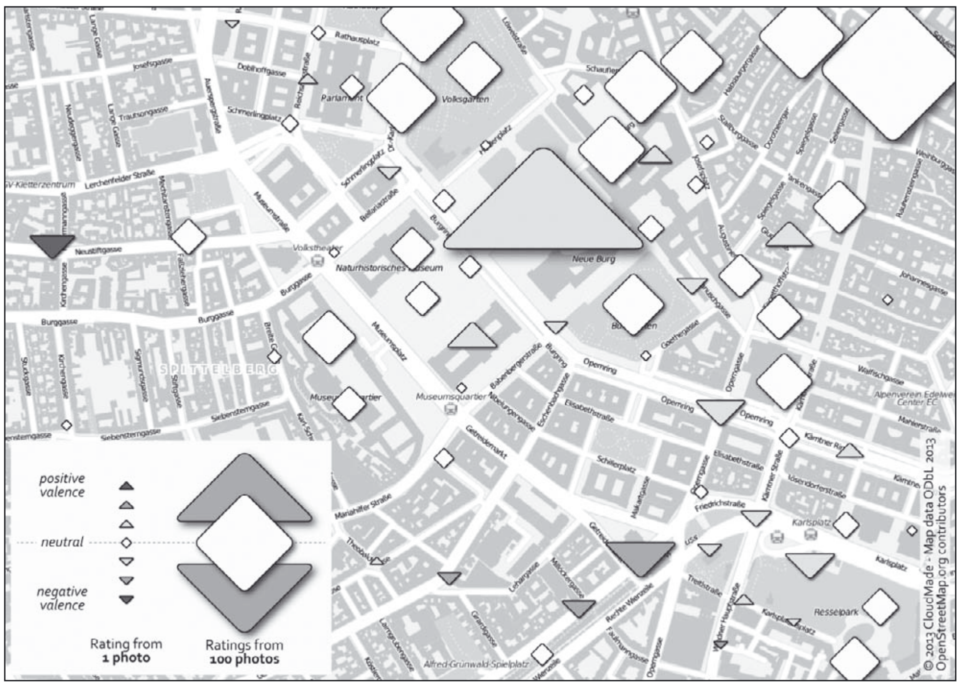

Fig. 2: People's affective responses towards environments. The grey shades of the markers indicate the valences of the photos.

value to the photo. Otherwise, we use Java WordNet Library to get synonyms of the word, and check whether one of the synonyms is in the AFINN word list. If yes, the valence value is also assigned to the photo. Finally, for each photo, we average all the valence values of its title, descriptions, and tags, and assign the result as the valence value of this photo.

Figure 2 shows the results in a map view. Each photo is visualised as a marker, and the grey of the marker indicates the valence of a photo (from positive valence to negative valence). In order to improve the legibility of the map view, nearby markers (photos) are clustered into an aggregated marker, whose grey indicates the averaged valence of these photos. The size of the aggregated marker is set according to the number of photos in this cluster.

Figure 2 reveals that different places are connected with different affective responses. Some places (e.g. parks) are perceived as pleasant (positive valence), while some others (e.g. main roads with busy traffic) are perceived as rather negative (unpleasant). Therefore, it might be interesting to correlate people's affective responses and the environmental characteristics of different places. More work should be done on this aspect.

In summary, this case study shows that social media data can be used to study humans' affective responses towards environments. However, we argue that in order to draw a clearer conclusion, more research efforts regarding the data analysis techniques should be made.

2.3 Case study 3: Identifying popular landmarks in Vienna

Recent years have seen many people publishing their travel information and experiences via social media, such as Foursquare check-ins and Flickr photos. This "self-reported" information can be used to derive the landmarks people visited when travelling to a new city. In this case study, we understand landmarks as attractions and locations frequently visited by people. The knowledge acquired from visiting these landmarks can be considered as people's first knowledge (or the first mental image in their mind) of the new environment. They act as anchor points for building other spatial knowledge (MACEACHREN 1991; GOLLEDGE 1999).

Conventional approaches of studying people's landmark preferences are questionnaires and surveys, which are very expensive and time-consuming. Ticket sale statistics are also used by many tourism bureaus to compile the rankings of attractions. This case study uses social media data to identify the landmarks people visited when travelling to a new city, and compares the popularity of different landmarks in summer and in winter.

Similarly, we employ the heuristic rule proposed in DE CHOUDHURY et al. (2010) to remove photos from local residents. We then use the list of popular attractions provided by the Vienna Tourist Board [Wiener Tourismusverband] as potential or candidate landmarks. This list of attractions was compiled according to the ticket sale statistics of 2009.[5] We then associate a Flickr photo to a potential landmark *p* whenever *p* is the closest landmark to the photo, and it was taken within 100 meters of *p*[6]. In line with Statistics Austria (*http://www.statistik.at/*), the period from May to October is defined as the summer season, while the rest as the winter season. After all these steps, we can order the popularity of different landmarks in both summer and winter according to the number of photos assigned to each landmark.

Figure 3 shows the results. The numbers attached to each landmark name denote the rankings of this landmark in summer and winter. Due to space restrictions, we only show the map view around the inner city. Therefore, some of the popular landmarks are not listed in the map view, such as Schloss Schönbrunn and Donauturm.

Figure 3 shows that the popularity of landmarks in summer is different from that in winter. Stephansdom is ranked the first in both summer and winter. However, the relative orders of other landmarks differ a lot. For example, Schloss Schönbrunn is ranked as the fifth in summer, while as the 13th in winter. This is consistent with what we expected: Due to the weather differences between summer and winter, places tourists visited in summer might be very different from those visited in winter. It is important to note that these results are generated by using the photos uploaded for Vienna during January 2007 and January 2011. When using photos from other time periods, the results might be slightly different.

This case study shows that social media data are useful for deriving the landmarks people visited when travelling to a new city, which can be then used to compare the popularity of landmarks in different seasons.

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[5] *http://en.wikipedia.org/wiki/Tourist_attractions_in_Vienna*
[6] This approach can be also improved by analysing the metadata (title, descriptions, and tags) of the photo.

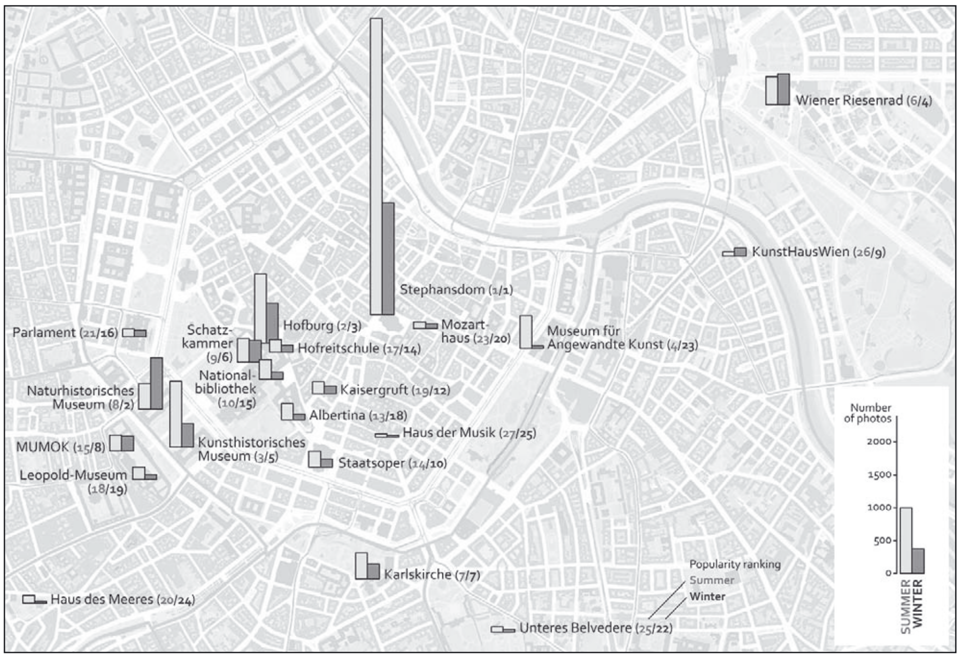

Fig. 3: Popularity of landmarks in summer and in winter. The numbers attached to each landmark name denote the rankings of this landmark in summer and in winter.

3 Socio-technical challenges of analysing social media data

While social media data have a high potential to be a new and significant source for studying people's perception and knowledge of environments, several challenges also exist when using social media data for studying these issues. In the following, we describe some of these challenges that we learned during the implementation of the above case studies, with a focus on the socio-technical ones.

The digital divide. While social media platforms are open to everyone, they are largely available for people who have access to the Internet, especially broadband Internet. For those who have access to broadband Internet, the usage of social media also differs greatly. A survey implemented by the Pew Research Center in late 2012 showed that young adults are more likely than others to use major social media (Duggan & Brenner 2013). In the meantime, the overall reach of social media is modest. For example, Twitter is used by about 16% of the US population, and most of these users are adults aged 18–29, African-Americans, and urban residents. In other words, users of social media are certainly far from a representative sample of the public. Therefore, results obtained from social media data should be carefully interpreted by considering these aspects, which is also the case for all the studies presented in Section 2.

Data quality. It is important to note that social media data are often very noisy, unstructured, and contain heterogeneous and multilingual content. For example, while many social media data are tagged with geographic location information, the actual location accuracy might be very poor due to the lack of quality-ensuring mechanisms in social media platforms. Therefore, data cleaning is needed before the actual data analysis of social media data. In order to process large datasets containing unstructured and multilingual content, existing techniques like natural language processing and text analytics should be improved. In the meantime, social media data often contain incomplete information. These data might be used to extract general trends of some phenomena. For drawing more detailed conclusions, heuristic rules or assumptions to derive the missing information are often needed, as what we have in differentiating local residents and tourists in Section 2. Biases caused by these heuristic rules and assumptions should be carefully analysed.[7)]

Influences caused by social media platforms/services. People contribute their UGC data via social media platforms, tools, and applications. These tools might affect the content of users' contributions, as well as their behaviours. For example, in Twitter, a person can "follow" someone else without his or her consent or mutuality, while in Facebook, "friending" requires mutual consent (TUFEKCI 2013). Therefore, when analysing social media data, attention should be also paid to these implicit and explicit structural biases brought by social media platforms.

Privacy. Privacy is another important issue to consider when analysing social media data, especially when the analysis is at an individual level. Anonymisation techniques might not work well for social media data. For example, if an anonymous user often posts messages to social media at a particular place in the early morning, and at another place in the afternoon around 14:00, it might be reasonable to assume that these two places are the user's home and office place, which can be then used to re-identify who the user is. Techniques like privacy-preserving data analysis (GIANNOTTI et al. 2013) should be introduced for analysing social media data.

In order to address the above challenges, interdisciplinary approaches integrating methodologies of geography, environmental psychology, computer science and other related fields should be developed and applied.

4 Conclusions and outlook

Recent years have seen many people using online social networking services in their daily life. As a result, more and more social media data about people's experiences and activities in various environments are available. This article proposes that social media data are a new and significant source for studying people's perception and knowledge of environments. Three case studies were developed to illustrate the

7) As we aimed to illustrate the potential of social media data for understanding people's perception and knowledge of environments, we did not address this aspect when discussing the case studies in Section 2.

potential of social media data on these aspects. Socio-technical challenges of analysing these data were also described and analysed.

Results of the case studies showed that social media data are useful for studying people's perception and knowledge of environments. Compared to the conventional methods such as empirical experiments and questionnaires which often use a small group of participants, analysing social media data enables us to investigate these issues with large-scale studies. In the meantime, we argue that in order to gain a better understanding of and also new insights into how people perceive and conceptualise environments, interdisciplinary approaches (e.g. geography, environmental psychology and computer science) should be developed and employed for analysing these social media data.

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