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An Advanced Systematic Literature Review on Spatiotemporal Analyses of Twitter Data

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Abstract

The objective of this article is to conduct a systematic literature review that provides an overview of the current state of research concerning methods and application for spatiotemporal analyses of the social network Twitter. Reviewed papers and their application domains have shown that the study of geographical processes by using spatiotemporal information from location-based social networks represent a promising and still underexplored field for GIScience researchers.

1 Introduction

Interactive social media platforms offer a tremendous amount of voluntarily, user-generated content. In particular, the potential of Twitter has been increasingly recognized by numerous research domains over the last years. Georeferenced Twitter data creates a promising opportunity for the research area of GIScience to understand geographic processes and spatial relationships inside social networks. However, the growing body of research works conducting Twitter data analysis is not clearly visible and not easy to locate. In particular, applications and applied methods for spatiotemporal analysis of Twitter data are not identifiable at first glance. Specific literature reviews, gathering knowledge and summarizing the scientific production for Twitter based research questions are currently lacking.

Therefore, the overall goal of this article is to close this research gap by providing an objective summary of the current state of the research concerning where Twitter in general has been used, for which specific use cases and what methods have been applied. The reviewed articles allow a more detailed evaluation regarding the potential of Twitter, but also summarize remaining challenges and investigate possible drawbacks. A key element of this review is to identify where solid research results already exist and where new research is needed. Cross-analyzing our reviewed papers concerning research disciplines, applications and methods, we identify current research foci and provide a solid foundation for further studies. Finally, recommendations for future research directions are given.

1.1 Background of VGI, Social Media and Location-Based Social Network

Emerging technologies have created new approaches towards the distribution and acquisition of crowdsourced information. The growing availability of mobile devices equipped with GPS sensors, high performing computers and broadband internet connections with advanced server

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and client-side key technologies, allows users to participate actively and create content through mobile applications and location-based services. The role of the user has changed from being either a producer or a consumer into being a rather dynamic prosumer (Tapscott 1996). The participation of individuals and their vast amount of generated data has been commonly known under the term Web 2.0 (O'Reilly 2009). Facilitated by new technologies, audiences are using their local knowledge without the need of prior expertise. Goodchild names this phenomenon 'Citizens as Sensors', where Volunteered Geographic Information (VGI) is created, assembled, and disseminated by individuals or groups with knowledge or capabilities using the Web 2.0 (Goodchild 2007). Within this interactive networked, participatory model of People as Sensors (Resch 2013), information is supplied free of charge and voluntarily. Haklay terms this development of new innovative social web mapping applications as the evolution of the GeoWeb (Haklay et al. 2008).

Social Networks are a key part of this development, incorporating new information plus communication tools and attracting millions of users. Boyd and Ellison (2007) outline the term Social Network Sites (SNS), typified by individuals who construct an online profile communicating with other users, sharing common ideas, activities, events and interests. Location-Based Social Networks further enhance existing social networks, adding a spatial dimension with location-embedded services. For example, users upload geotagged photos via Flickr, checking in at a venue with Foursquare or commenting on a local event via Twitter. Geoinformation extracted from these Location-Based Social Networks is usually included under the umbrella of Volunteered Geographic Information (Sui and Goodchild 2011). However, Harvey (2013) argues that this would be more precisely labeled as "contributed" data, since people do not consciously volunteer their data, but generate it in the process of using the platforms for their particular purposes.

In the case of Twitter, users can post short-status messages with up to 140 characters and may include photo attachments, which are called "tweets". These posts can contain specific syntax such as hashtags (#) as a keyword or term assigned to a topic the users are discussing or commenting about. Furthermore, a user can subscribe to "follow" or become a "follower" of other users' tweets with the possibility of replying directly (@) to all Twitter posts. According to Twitter, about 271 million monthly active users are generating an average of 500 million tweets per day (https://about.twitter.com/company). With the permission of the user, each tweet contains a corresponding geo-location acquired from the GPS sensor within the mobile device. These location-driven social structures allow mobile device owner with ubiquitous internet access to exchange details of their personal location as a key point of interaction (Zheng 2011). Location-Based Social Networks are bridging the gap between our physical world and online social network services containing three layers of information according to Symeonidis et al. (2014): (1) a social network (user layer); (2) a geographical network (location layer); and (3) a semantic metadata network (content layer).

Therefore, user posts in Twitter represent a spatiotemporal signal (geolocation and timestamp of tweet) with a semantic information layer (content of tweet message). After the user registration, all tweets can be collected in real-time through the official Twitter streaming API (https://dev.twitter.com/docs/api/streaming). The API query allows the filtering of keywords and individual user posts to preselect tweets as well as the possibility of obtaining only georeferenced Twitter messages within a predefined bounding box. Analyzing this spatiotemporal information layer, which is a by-product of individual people's social interaction, may lead to new insights of understanding spatial structures and underlying patterns. This interdisciplinary and relatively new research field of Location-Based Social Networks shows a lack of commonly used online databases and available literature sources. Systematic reviews therefore might assist structuring and providing a comprehensive summary of currently existing literature. This review seeks to gain new knowledge and insights into the current state of research of Twitter analyses, regarding involved academic disciplines, primarily reviewed applications and used methods. One benefit of this review will be the ability to detect current research foci allowing the transfer of established methods from various disciplines into other disciplines and enhancing new applications. Finally, the review will provide all stakeholders with further knowledge enabling an interdisciplinary research exchange.

1.2 Existing Literature Reviews

A non-systematic keyword search looking for the term "systematic literature reviews" in common electronic GIS journal libraries was conducted initially, in the following journals: International Journal of Geographic Information Science, International Journal of Remote Sensing, Photogrammetric Engineering and Remote Sensing, Computers and Geosciences, Transactions in GIS, GeoInformatica, Geomatica – i.e. only journal papers which were ranked as a number one GIScience journal according to the Delphi Study by Caron et al. (2008) were selected. Surprisingly, besides literature surveys and basic non-systematic reviews from other disciplines dealing with geographic information systems, no journal articles conducting a systematic literature review with relevance to GIScience have been found. This preliminary outcome underlines the need for further research conducting a systematic literature review in GIScience.

Related to geographic information science, Horita et al. (2013) assessed the current state of research for a conference paper analyzing VGI for disaster management and applying a systematic literature review including a screening process of important literature databases. Roick and Heuser (2013) provided a general but non-systematic review article about the current research on Location-Based Social Networks, stating the need of further studies on investigating how social networks can be applied to specific use cases. Blaschke and Eisank (2012) conducted a non-systematic keyword-based literature search comparing the terms "GIS" and "GIScience" and their total number of citations over time. However, existing literature reviews in the GIScience field have been performed in a rather non-systematic manner, with a lack of statistical techniques including metadata analysis. To the best of our knowledge, no systematic literature reviews have been published up to this moment in well-known journals in the field of GIScience.

2 Review Method

This review will follow the guidelines developed by Kitchenham and Charters (2007) and Kitchenham et al. (2009), dividing the research into three main phases: (1) planning the review; (2) conducting the review with the selection of studies from electronic databases; and (3) reporting the final review results itself.

The flowchart review model in Figure 1 visualizes our automatic workflow approach. The following paragraphs and sections are divided according to the review process shown in the flowchart of Figure 1. Due to limited space, the detailed procedure and methods of the literature review, including all intermediary and derived results have been documented in a review protocol and are published as a separate technical report (http://koenigstuhl.geog.uni-heidelberg.de/publications/2014/Steiger/Twitter_review_technicalreport.pdf). The detailed review method steps have been black-boxed in Figure 1 and are part of the external technical report.

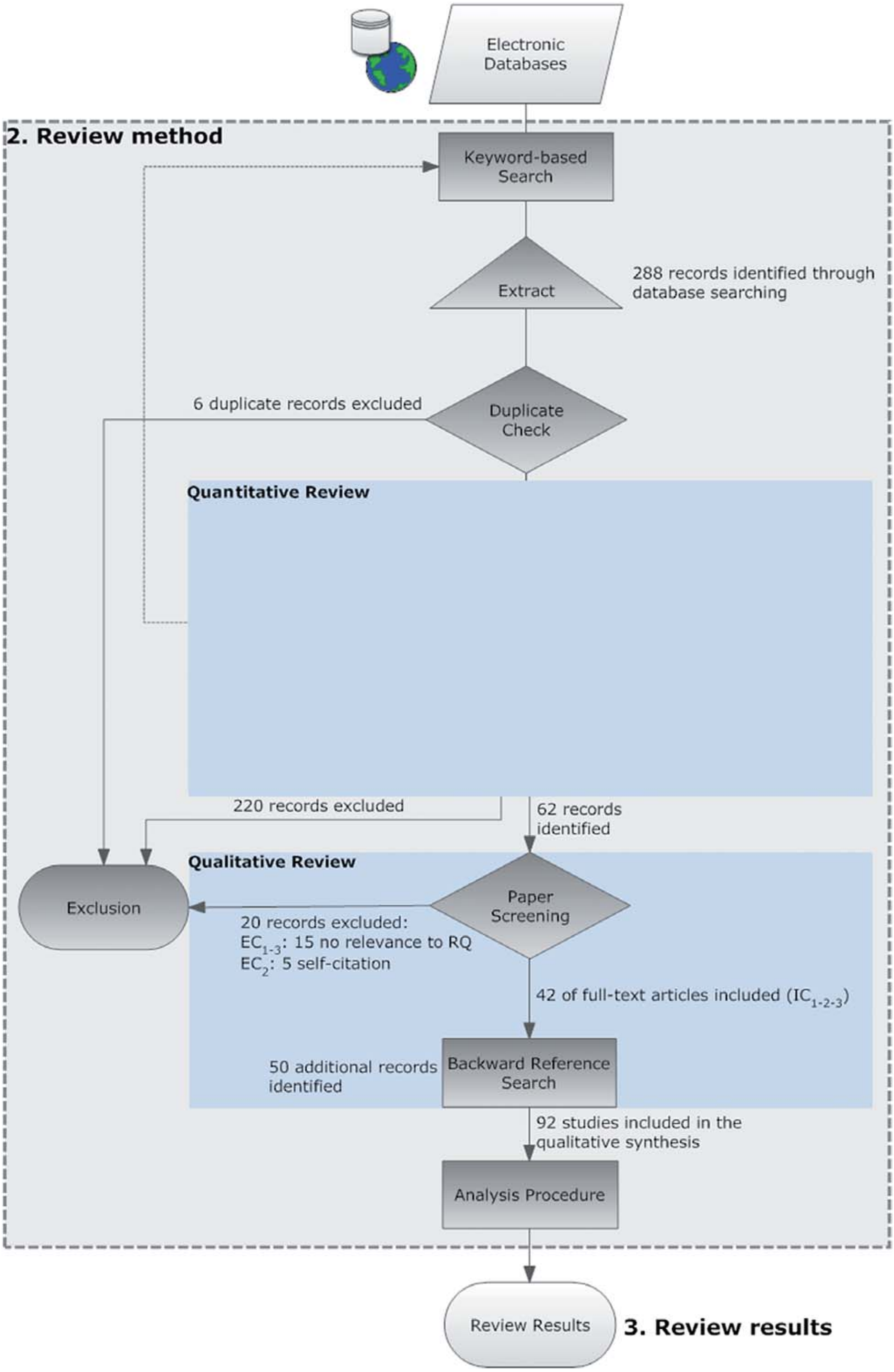

Figure 1 Flowchart review process and number of included and excluded papers in each step

Drafting a clear and concise research question is an essential task needed to successfully identify primary studies providing a detailed state-of-the-art report (Okoli and Schabram 2010). As the review objectives are to extract use cases, focused research areas and methods when utilizing Twitter, the following three research questions have been selected:

RQ 1: Which of the academic disciplines are mainly focused on researching Twitter?
RQ 2: What are the application domains where Twitter has been used?
RQ 3: What are the methods used to analyze data from Twitter?

Application domains are defined as the primarily identifiable research field of Twitter applications for each paper.

The initial step consists of selecting eligible literature sources based on following criteria:

- Consideration of journal, workshop and conference proceedings published between 2005 and September 2013 in English;
- Selection of multiple digital libraries with relevance to information research identified by Brereton et al. (2007) and further supplemented with GIScience relevant digital libraries.

The electronic database search with defined keywords was conducted and included all papers published up until 30 September 2013. Furthermore, test reviews with preliminary trial searches were carried out in order to detect and minimize bias concerning the defined search strings or during the subsequent data extraction process.

Table 1 depicts our initial 288 and 92 final reviewed papers concerning the publication source. Duplicate search results found in multiple electronic databases have been excluded. Papers appearing in several electronic databases (e.g. in the Google Scholar search engine for publications and in the Web of Knowledge) will only be included once, storing unique search results. The backward reference search in Table 1 is a result of the further qualitative review (see Technical Report).

Table 1 Used electronic databases with included and excluded papers during the review process

Source	URL	Unique Search Result	Result Paper Screening	Backward Reference Search	Final Review
IEEE Library	*http://www.ieeexplore.ieee.org*	36	5	9	14
ACM Digital Library	*http://dl.acm.org*	149	20	21	41
AIS Electronic Library	*http://aisel.aisnet.org*	4	1	0	1
Google Scholar	*http://scholar.google.de*	12	8	8	16
Science Direct	*http://www.sciencedirect.com*	12	0	0	0
Elsevier	*http://www.scopus.com*	23	3	1	4
Springer Link	*http://www.springerlink.com*	9	0	3	3
Taylor and Francis	*http://www.tandfonline.com/*	15	0	0	0
Wiley Online Library	*http://onlinelibrary.wiley.com*	2	1	1	2
Web of Knowledge	*http://www.webofknowledge.com*	18	2	0	2
AAAI	*https://www.aaai.org/*	2	2	7	9*
Total		**282**	**42**	**50**	**92**

*Papers from the Association for the Advancement of Artificial Intelligence (AAAI) have been extracted from the text analysis but not detected within the metadata analysis. The qualitative review has shown a relevance of these articles to our research questions and therefore all papers have been included

Table 2 Defined inclusion and exclusion criteria during the qualitative review

IC_1:	Papers clearly depicting their research applications of Twitter data (RQ 1)
IC_2:	Papers clearly describing their used methods concerning the exploration, extraction, processing, validation and aggregation of Twitter data (RQ 3)
IC_3:	Papers being listed in previous selected electronic databases (Table 1)
EC_1:	Papers not explaining methods nor their applications of Twitter data usage (RQ1 and RQ3)
EC_2:	Duplicate content, i.e. papers covering the same research about Twitter from the authors (e.g. a journal paper containing only minor extensions to a conference paper)
EC_3:	Papers not being listed in previous selected electronic databases (Table 1)

The remaining studies (n = 92) have been qualitatively reviewed. A tabulated spreadsheet has been developed to assist the review process. All results are documented in a detailed review table, collating information from all 92 papers aiming to answer our initial research questions. Reviewed papers and their specific applications (RQ 2) (as shown in Figures 5 and 6), have been categorized by analyzing the primarily stated research application from the paper. The applied methods (RQ3) have been classified using the defined topic types according to Kitchenham and Charters (2007).

A practical screen of included papers by reading the full-text, furthers the review by examining methods and use cases. The inclusion (IC) and exclusion criteria (EC) for the qualitative review are listed in Table 2.

During the paper screening process, 42 papers were included which show relevance to our previous formulated research questions (IC_1, IC_2 and IC_3). Fifteen papers not explaining their methodological approach or application of Twitter fall within the exclusion criteria (EC_1). Another five papers have been excluded because of duplicated content (EC_2). These cross citations have not been excluded quantitatively in the metadata- and text-analysis previously as they are strongly semantically close. Forty-two papers remain for the further analysis.

3 Review Results

Analyzing the year of publication for all included papers in the final review, a constantly increasing amount of Twitter research articles have been published during the reviewed time period (01/01/2005–30/09/2013). Between 2009 and 2012 the quantity of published papers has more than tripled from 27 to 84 (Figure 2). As the review includes all works published until September 2013, a similar trend concerning the number of papers for the whole year 2013 can be postulated. The majority of finally included and reviewed papers have been published between 2011 and 2012 (53 papers for both years).

In the following sections, our research questions will be answered.

3.1 RQ 1: Which of the Academic Disciplines are Mainly Focused on Researching Twitter?

All papers' metadata has been analyzed to find out from which academic disciplines authors are contributing research results on Twitter in general (Figure 3). Papers have been classified according to academic disciplines based on available metadata within the paper, where authors state with which department or research field they are affiliated. If not provided inside the

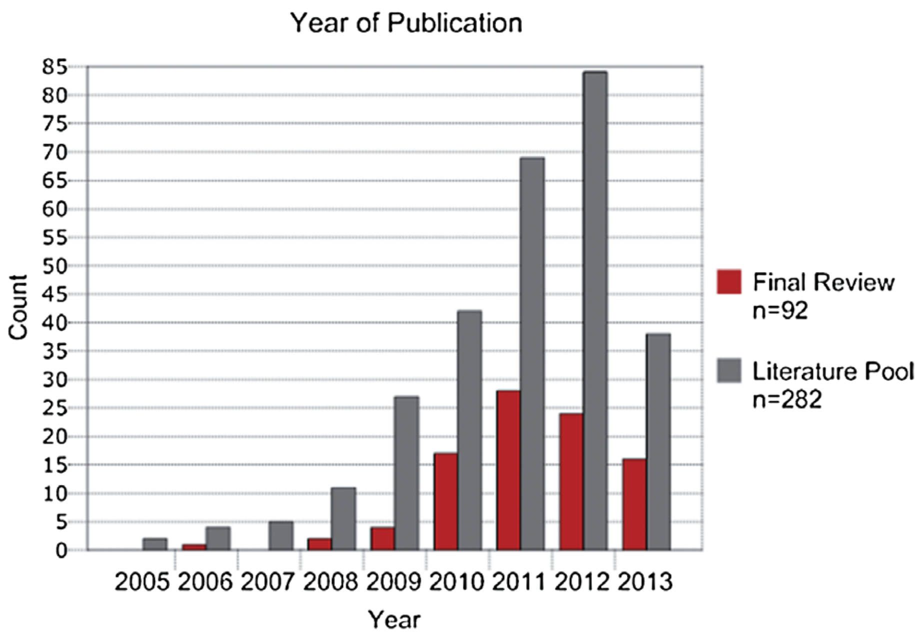

Figure 2 Comparison year of publication of initially selected papers (n = 282) with results from the final review (n = 92)

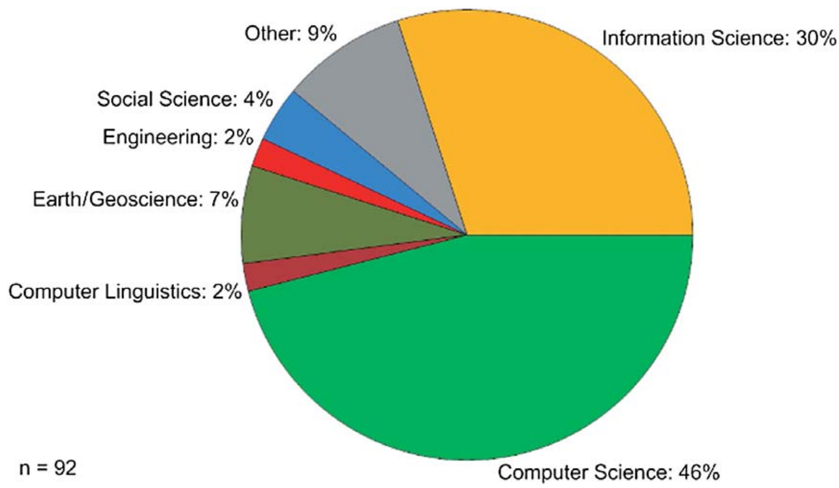

Figure 3 Classification of papers according to authors' academic research disciplines

papers, the authors' affiliated faculty or department was investigated through an online search. Forty-six percent of our reviewed papers have been published by researchers working in the Computer Science field, along with 30% from the field of Information Science. Other research disciplines such as Earth- and Geoscience (7%), Social Science, Engineering and Computer Linguistics have only a minor occurrence (less than 4% each). In 9% of the papers authors have a multi-disciplinary background. In Figure 4 the temporal evolution of reviewed studies

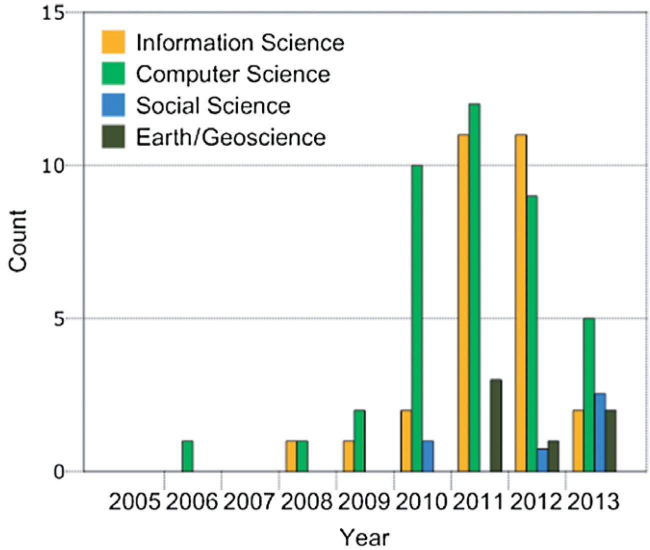

Figure 4 Yearly breakdown of publication count in different academic disciplines

(Figure 2) according to their academic discipline (Figure 3) have been combined and analyzed. Due to the sparseness and small number of studies for some disciplines only the most frequently occurring ones (above 4%) have been visualized. The majority of the reviewed studies were published between 2010 and 2013 mainly from an information and computer science background. From earth/geoscience and social science disciplines only a few studies have been published since 2011.

3.2 RQ 2: What are the Application Domains where Twitter has been Used?

When focusing on primary applications of every paper (Figure 5), more than 46% of the papers have been classified as research on event detection, 14% of the papers deal with social network analysis and investigate individual user characteristics and their social relationships within a network. Thirteen percent focus on retrieving direct or indirect geolocation information from Twitter defined as location inference, while 27% of the papers do not have a specific context of application (Figure 5). Within the subfield of event detection and the investigation of abnormal spatial, temporal and semantic tweet frequencies, disaster- and emergency management has been the primarily identified application in 27% of all reviewed studies. Twitter research for traffic management has been the application in 14% of reviewed studies, while 5% are investigating Twitter for disease/health management. Within 49 papers we were able to extract the geographic location where Twitter data has been collected on a country level and in a few cases on a city level. Almost 24 papers obtain and analyze Twitter datasets inside the USA (Figure 6). Six papers collect Twitter data on a city-scale for New York. The seven papers covering Twitter data for Japan and the two papers retrieving social media data for Haiti, use Twitter in the context of disaster management.

3.3 RQ 3: What are the Methods Used to Analyze Data from Twitter?

Before investigating the research methodologies within all reviewed papers, we first examine exactly which information from Twitter data has been used. The applied methods are strongly

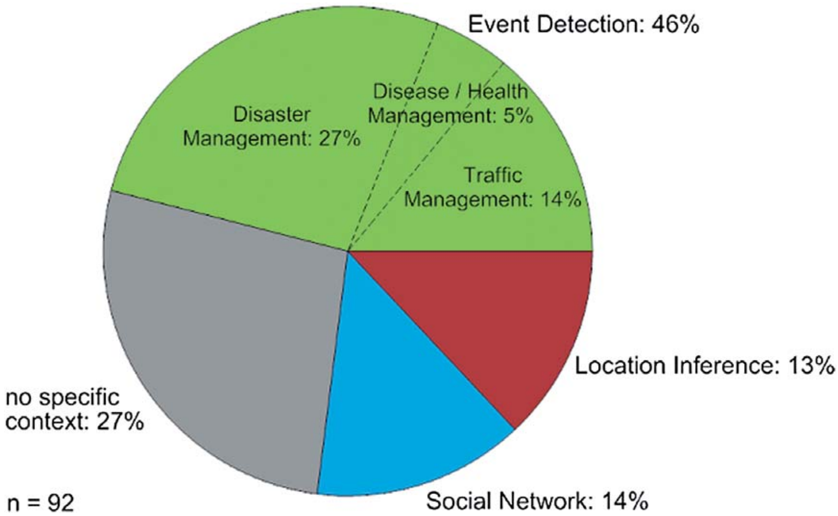

Figure 5 Specific application domain of reviewed papers

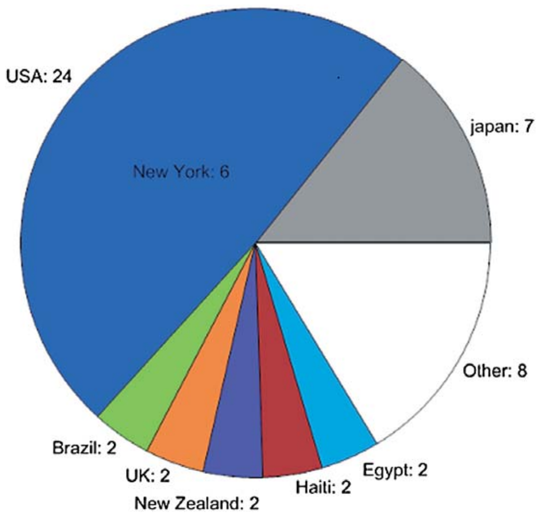

Figure 6 Streamed Twitter data per country (n = 51)

dependent on the information content of the Twitter input data (Figure 7). Thirty-three percent of the papers use all information layers, including the tweet message, the geotag (geospatial information), and the timestamp. The main focus of these papers is a *spatio-temporal and semantic analysis*. Ten percent of papers focus on researching *spatio-temporal* information in Twitter not including semantic analysis. Therefore, 43% are working with spatial data from tweets. Fifty-seven percent of articles only consider the semantic information of the tweet itself without spatial information. These papers analyze the content of tweets and construct a semantic network to enrich non-spatial posts with geographic information to infer locations. Within these papers, four papers analyze solely the Twitter posts to infer geographic locations and identify geographic landmarks from textual information. One paper (Watanabe

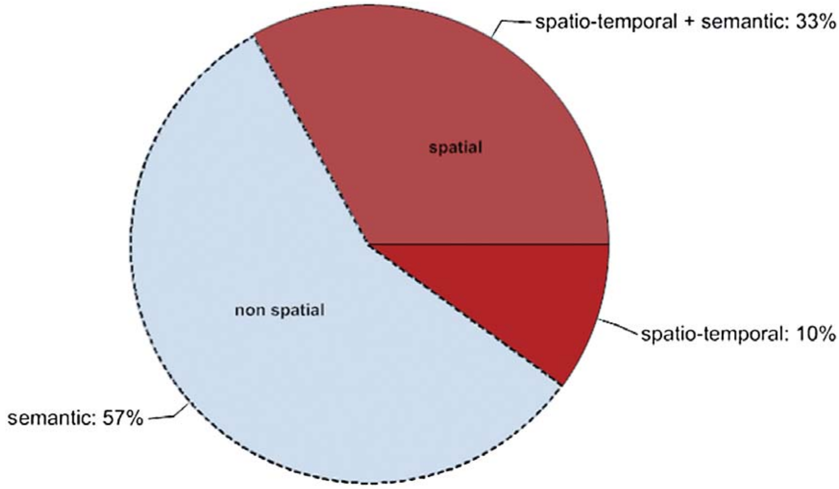

Figure 7 Information used from Twitter in the reviewed papers

et al. 2011) furthermore analyzes semantic tweet frequencies to assign and locate non-geotagged tweets to events with a geographical reference.

Ten papers also analyze follower and following activities of the Twitter user, five conduct a hashtag analysis and two a URL analysis. Descriptive metadata from Twitter including user profiles and personal user activities are a main research domain to conduct a *metadata analysis*. This user centered approach, applied within six of the reviewed papers, includes the analysis of Twitter profiles metadata and tweet posts as well as social relationships (follower/following), to predict individual user locations and to cluster similar users.

When focusing on the temporal evolution of used information from Twitter (Figure 8), the majority of reviewed papers between 2006 and 2011 conduct research on Twitter by using non-spatial (semantic) information. Simultaneously, only one reviewed paper in 2009 focuses on researching Twitter data using spatial information. Thus, from 2010 onwards the amount of reviewed papers utilizing spatial information has increased, and it passes non-spatial Twitter analyses in 2012. The number of reviewed papers researching spatiotemporal and semantic information is growing with the number of papers focusing on spatial aspects of Twitter data.

As shown in Figure 9, 40% of the articles have a technological background with a focus on investigating and developing methods of exploring, extracting, validating and aggregating Twitter data, while 20% of the reviewed studies go one step further, providing a conceptual model by implementing a system architecture to collect and process data from the Twitter streaming API. The remaining 40% of the papers focus on the application side of Twitter. Taking a closer look at the applied methods, 55 papers out of 92 investigate methods of event detection in Twitter (Figure 10). Methods analyzing the social network of Twitter together with approaches to infer location are also frequent methodological applications (applied in 13 papers). Four papers work on topic detection and no specific method was identified for 11 papers.

The specific methods used in all the reviewed papers are now summarized. The main purpose of all applied methods is to acquire knowledge from Twitter data by considering the characteristics of the dataset. Information retrieved from Twitter data is spatiotemporally and semantically uncertain. Focusing on the sematic content of Twitter data, the textual component of Tweets is a cohesive string of words. These word vectors are relatively vague and

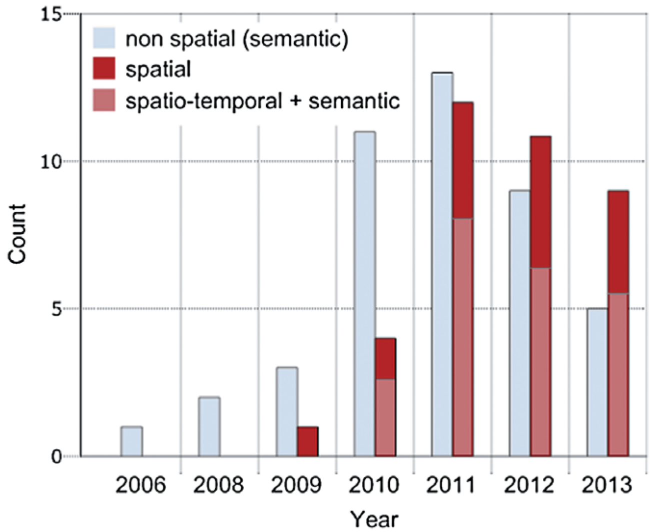

Figure 8 Yearly breakdown of paper count according to the information used from Twitter

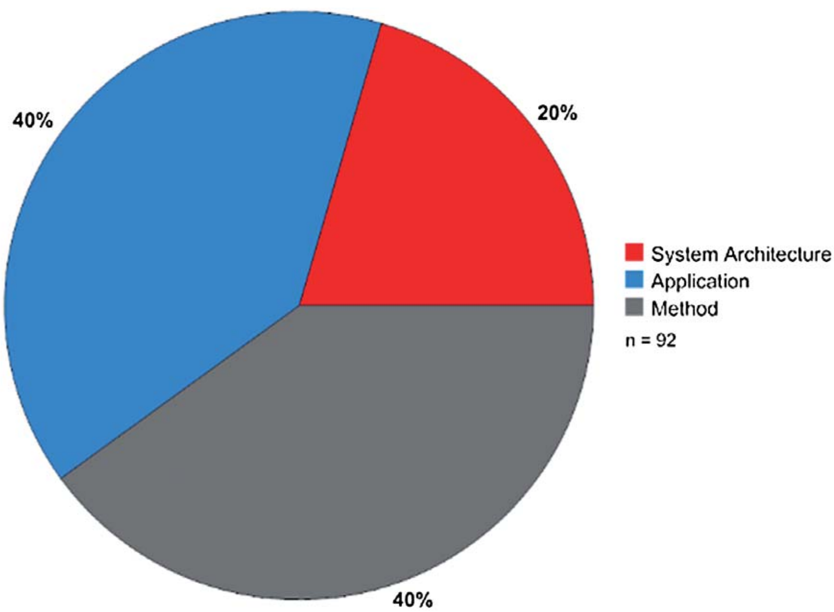

Figure 9 Classification of papers according to applied methods (n = 92)

semantically uncertain. Therefore methods have been applied by either manually filtering terms and keywords or by integrating a Natural Language Processing step (Kosala and Adi 2012; Quercia et al. 2012; Corvey et al. 2010; Wanichayapong et al. 2011). Text mining methods such as term frequency (Hecht et al. 2011), term frequency–inverse document frequency (Wang et al. 2012; Jackoway et al. 2011; Weng and Lee 2011) and term-ranking algorithms (Gupta and Kumaraguru 2012) have been used to create semantic weighting factors for

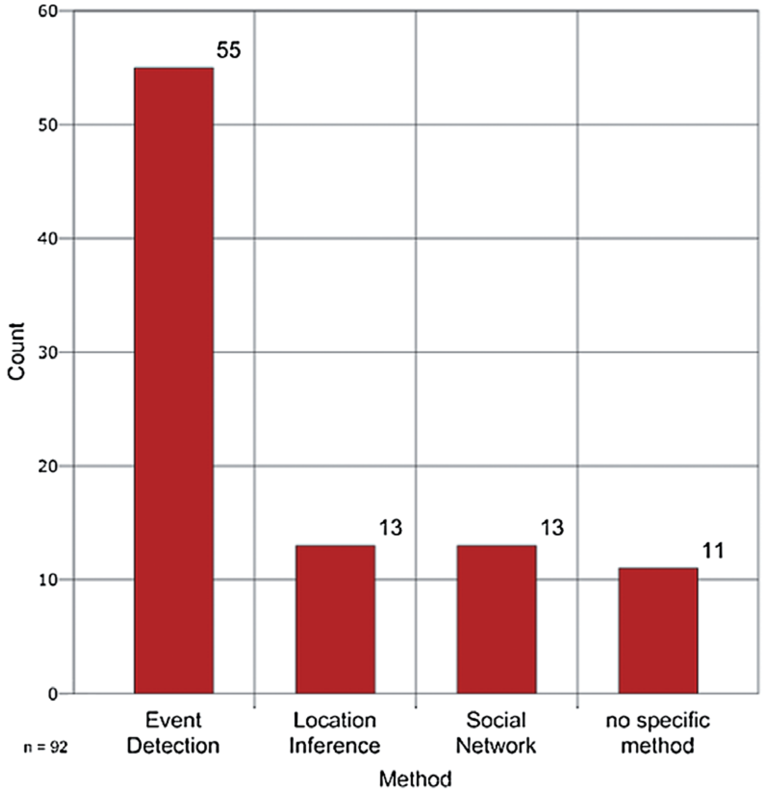

Figure 10 Paper and categories of methods (n = 92)

tweets. Further semi-automatic ontologies (Sofean and Smith 2012) have been generated from the tweet corpus to extract and identify semantic relationships (Watanabe et al. 2011). Other approaches used in the reviewed papers include semantic classification algorithms like Named-Entity Recognition (Abel et al. 2012; Finin et al. 2010; Michelson and Macskassy 2010; Gelernter and Balaji 2013), supervised machine learning like Naïve Bayes (Zielinski and Bügel 2012; Wang et al. 2007), or maximum entropy classifier (Go et al. 2009) for pattern recognition. Latent Dirichlet Allocation as a probabilistic topic modeling has been used in several papers (Chae et al. 2012; Kling et al. 2012; Zhao et al. 2011; Pennacchiotti and Popescu 2010; Ferrari et al. 2011; Weng and Lee 2011), retrieving textual information for a set of topics from tweets. Several models consider the spatial component of semantic distributions proposing Spatial Latent Dirichlet Allocation (Pan and Mitra 2011) and Location aware topic modeling (Wang et al. 2007). Since the location information from Twitter might be inaccurate because of spatiotemporal uncertainties or incorrect due to mobile device characteristics, methods have been applied to infer spatially reliable information. For spatial attributes from Twitter (georeferenced tweets) regression models have been developed to correlate abnormal tweet frequencies with real world events (Takhteyev et al. 2012; Veloso and Ferraz 2011). Gazetteer-based approaches have been used to infer indirect locations from Twitter attributes (Zielinski and Middleton 2013; Ribeiro et al. 2012). Georeferenced tweets have been Kalman filtered (Sakaki et al. 2010) and clustered applying Density-Based Spatial Clustering (Boettcher and

Lee 2012). Based on geotag and semantic content, tweets have also been classified using Support Vector Machines (Ritterman et al. 2009; Zubiaga et al. 2011; Starbird and Muzny 2012; Sakaki et al. 2010).

3.4 Cross Analysis

In the following paragraph a cross analysis has been performed, investigating where methods have been extracted and sorted according to their category of application. However, not all 92 qualitatively reviewed papers can be quoted herein. Table 3 includes a detailed description of the outcomes of each reviewed study dealing with the spatial aspect of Twitter data.

3.4.1 Event detection

Within the subdomain of an event detection, researchers are investigating on detecting abnormal spatial, temporal and semantic tweet frequencies and patterns in real-time using Twitter as a social sensor for real world events (Chae et al. 2012; Yardi and Boyd 2010). Semantic information has been the predominant information layer used for event detection. Cui et al. (2012) work on semantic topic detection for events by analyzing popular hashtags. Several studies focus on the semantic tweet content using Natural language processing (Corvey et al. 2010). Becker and Gravano (2011) and Jackoway et al. (2011) identify real-world event and news content on Twitter by extracting and classifying topics using tf-idf and Naive Bayes Classifier. Weng and Lee (2011) cluster wavelet-based signals in Twitter and classify events by applying tf-idf as well as the LDA topic modeling algorithm (Blei et al. 2003). Kling et al. (2012) research urban topic modeling with LDA and spatio-temporally clustered Twitter data in New York to detect events. Lee and Sumiya (2010) study user behavior patterns in Twitter measuring geographic regularities detecting geo-social events and identifying Regions of Interests (RoI). Boettcher and Lee (2012) differentiate events based on geographical scales by counting average daily keyword frequencies over space using DBSCAN clustering algorithm (Ester et al. 1996) and classify terms according to their relevance to a local event. Abel et al. (2012) also semantically filter keywords and classify information on Twitter applying Named-entity recognition. Hughes and Palen (2009) focus on Twitter metadata performing a user analysis and classification including tweet response rates for mass convergence events. Starbird and Muzny (2012) analyze mass disruption events using the Support-Vector Machine (SVM) Learning algorithm to classify user tweeting "on ground" and "not on-ground" for the Occupy Wall Street movement in New York.

Disaster/emergency management. In the area of disaster/emergency management spatiotemporal and semantic information have been mainly used to analyze Tweets. Thomson et al. (2012) categorizes tweets and measures tweet proximities comparing different sources of information and assessing reliability of Twitter for the Fukushima nuclear power plant incident. De Longueville and Smith (2009) conduct a spatio-temporal analysis of Twitter tweets for a fire event in France. Murthy and Longwell (2013) explore the temporal frequency distribution of tweets per country for disasters. Together with MacEachren et al. (2011), who develops a system architecture for situation awareness, they are both applying methodologies for the earthquake in Haiti. Twitter as an *earthquake detection* and geolocation system was first introduced bv Sakaki et al. (2010) and was adapted by Crooks et al. (2013). Methods in this work include a Kalman and partioning filter of tweets together with a SVM classification to estimate the earthquake location and to derive a hazard trajectory from tweets. Sakaki et al.

Table 3 Detailed review and study overview of papers conducting spatiotemporal Twitter analyses

Study	Application	Used information	Method	Study overview	Limitation
De Longueville and Smith (2009)	Disaster/ Emergency Management	tweet (including URL analysis) and metadata (user profile)	Landmark based geographic feature extraction by filtering tweets with a set of keywords	Case study fire event in France: posts are temporal and spatial accurate to real world event, they contain indirect geographical information and posted URLs refer to media and news portals	Only manual keyword-based filtering
Murthy and Longwell (2013)	Disaster/ Emergency Management	tweet (including URL and retweet analysis) and meta data (user profile)	Simple extraction of user defined geographic locations using a geocoding service and filtering of tweets with a set of keywords	Case study flood event in Pakistan: Majority of flood related tweets are linked to traditional media sources and generated within Pakistan followed by western countries (UK, US, and Canada)	Only manual keyword-based filtering
MacEachren et al. (2011)	Disaster/ Emergency Management	tweet, geotag and timestamp	Aggregated grid-based count of georeferenced tweets which have been filtered with a set keywords	Case study earthquake (Haiti): Approach was able to extract and validate locations of tweets during an earthquake event	Only manual keyword-based filtering
Sakaki et al. (2010)	Disaster/ Emergency Management	tweet, geotag and timestamp	Kalman filtering of tweet locations which have been textual classified using SVM	Earthquake location estimation and typhon trajectory estimation from tweets is possible, 96% of earthquakes larger than intensity scale 3 detected from tweets	
Crooks et al. (2013)	Disaster/ Emergency Management	tweet, geotag and timestamp	Calculation of angular distances for each georeferenced tweet to real word epicenter, Tweets have been filtered with a set of keywords	Case Study earthquake (US): within 2 minutes 100 accurately geolocated tweets have been posted. Tweets originate near the epicenter and slowly diffuse over the country	Earthquake intensity cannot be quantified through Twitter posts
Earle et al. (2011)	Disaster/ Emergency Management	tweet, geotag and timestamp	Spatiotemporal keyword filtered tweet frequency analysis to detect spatial outliers	Earthquake detections from official geological surveys have been compared worldwide with Twitter information. Out of 5,175 earthquakes only 48 have been detected within Twitter (average detection delay of 2 minutes).	Only manual keyword-based filtering
Stefanidis et al. (2011)	Disaster/ Emergency Management	tweet, geotag and timestamp	Spatial hotspot detection of tf-idf word frequency analyzed tweets	Geopolitical events (e.g. riots) and hotspots of other crises have been detected and information dissemination within Twitter studied in order to improve the situation awareness and emergency response	
Terpstra (2012)	Disaster/ Emergency Management	tweet and geotag	Mapping of georeferenced tweets which have been filtered with a set of keywords	Case study festival in Belgium: event information for a severe storm was extracted and insights for improving disaster management and relief have been demonstrated	Simple mapping of georeferenced tweets, only manual keyword-based filtering
Chae et al. (2012)	Disaster/ Emergency Management	tweet, geotag and timestamp	Seasonal-trend decomposition of LDA semantic topic modeled tweets to detect abnormal spatiotemporal pattern	Events have been detected for three case studies using location information and textual information	
Kling et al. (2012)	Event Detection	tweet, geotag and timestamp	Spectral clustering and geographical heat maps of LDA semantic topic modeled tweets	Case study New York: temporal patterns and functions of urban areas have been detected	LDA topic model parameter set manually

Lee and Sumiya (2010)	Event Detection	geotag and timestamp	Central points of k-means cluster used to form voronoi diagrams, frequency analysis of voronoi cells	Case Study Japan: unusual crowd activities assuming abnormal events (e.g. earthquake) have been detected by observing geographic regularities within defined regions.	K-means clustering parameter of regions set manually No textual information analyzed
Boettcher and Lee (2012)	Event Detection	tweet, geotag and timestamp	Keyword frequency analysis of DBSCAN clustered tweets	Events have been detected with a precision of 68% by estimating the average tweet frequency of keywords per day in and around a potential event area.	Only manual keyword-based filtering DBSCAN parameter set manually
Veloso and Ferraz (2011)	Disease / Health Management	tweet, geotag and timestamp	Tweets have been filtered with a set of keywords and ST-DBSCAN has been applied	Case study Brazil: strong correlation ($r^2 = 0.95$) between spatiotemporal distribution of tweets related to dengue fever cases and official statistics	Only manual keyword-based filtering
Lampos and Cristianini (2010)	Disease / Health Management	tweet, geotag and timestamp	Urban center matching of georeferenced tweets within 10 km radius, n-gram textual analysis	Case study UK: significant correlation ($r^2 = 0.95$) between the flu epidemic related posts on Twitter with the official health report	
Wanichayapong et al. (2011)	Traffic Management	tweet, geotag and timestamp	Geocoding of georeferenced tweets to road-related attributes, Tweets have been filtered with a set of keywords	Point and link-based traffic incidents from Twitter have been classified into road segments with 93% accuracy and on points with 76% accuracy.	Only manual keyword-based filtering Human categorization of traffic news
Li et al. (2011)	Location Inference	tweet, geotag and timestamp	POI Matching and ranking method	Case study Chicago (US): the developed ranking method predicted the POI tag of tweets bases on textual information and time	Dataset partially too sparse to annotate every tweet to POI
Lee and Hwang (2012)	Location Inference	geotag, timestamp and metadata (user profile)	Text based grouping method correlating georeferenced tweet with user set profile location	Correlation of user profile locations and georeferenced tweets showed that more than half of all tweets are posted in the user's hometown. 30 % of Twitter users did not have any posts near their set profile location.	User profile location are limited (30 characters) Use of different languages in Twitter aggravates textual processing
Hiruta et al. (2012)	Location Inference	tweet, geotag and timestamp	Classification of georeferenced tweets called Place-triggered georeferenced Tweets. Tweets have been filtered with a set of keywords	Tweets have been successfully classified into type of places (whereabouts of people, food, weather, back at home, and earthquake). Detection of place triggered georeferenced tweets had 82% accuracy.	Supervised classification with manual tweet labeling by test persons
Dalvi et al. (2012)	Location Inference	tweet, geotag	Probabilistic Distance-based model with parameter inference using EM algorithm. Tweets have been filtered with a set of keywords	Language and distance based model was able to infer and match tweets with a real objects geographic location (example POI restaurants)	Only manual set keyword-based filtering
Cranshaw et al. (2012)	Social Network	tweet, geotag and timestamp	Spectral clustering of georeferenced check-ins posted through Twitter. Activity have been classified according to check-in venue categories	Case study Pittsburgh (US): social media check-ins and qualitative interviews revealed collective social behavior of people differentiating a city into "Livehoods" which correspond to municipal boundaries	Aggregation of individual user behavior into collective movement

(2010) and Earle et al. (2011) monitor earthquakes in China (Sichuan province), Japan and Indonesia, in real time with a semantic and temporal tweet frequency analysis. Zielinski and Bügel (2012) use a multilingual language model with a Naive Bayes Classifier to semantically detect earthquake events posted on Twitter. Gelernter and Balaji (2013) work with Named-entity recognition to detect and geocode geographic content from an earthquake in New Zealand. Stefanidis et al. (2011) analyze ambient geospatial information for a *crisis event detection* in Egypt (Cairo) performing spatio-temporal and social network analysis. Gupta and Kumaraguru (2012) analyze tweets during riots with a news ranking engine validating the credibility of information by checking the posts and user profile metadata. *Flood, storm and hurricane detection* are also common applications where methods have been developed. Terpstra (2012) conduct a spatio-temporal analysis on Twitter data during a severe storm at a mass event. Zielinski and Middleton (2013) obtain and classify Twitter datasets during a tsunami in the Philippines and a flooding event in New York using a gazetteer based automatic geocoding approach. Chae et al. (2012) describe a term-based filtering and anomaly detection in Twitter for a hurricane and earthquake event.

Disease/health management. Ritterman et al. (2009) consider Twitter to be a proxy to predict market prices during a swine flu pandemic analyzing tweet content with a SVM classification. Sofean and Smith (2012) observe Twitter for disease reports from users building an ontology of medical terms combined with a SVM classification. Veloso and Ferraz (2011) also extract keywords from tweets to measure semantic similarities and spatio-temporally locate incidents of dengue fever in Brazil. Lampos and Cristianini (2010) follow a similar approach in the UK, using a correlation regression model to match up Twitter posts with real world disease reports.

Traffic management. Wanichayapong et al. (2011) mine Twitter data to derive spatio-temporal traffic-related information using a NLP and keyword filtering method to match traffic information from Twitter on road networks in Thailand. Sakaki and Matsuo (2012) have a similar approach in Japan with an additional classification of driving information from Twitter. Ribeiro et al. (2012) detect and locate traffic events with Twitter by georeferencing traffic-related tweets with a gazetteer. Kosala and Adi (2012) also collect traffic related Twitter data using a NLP. Furthermore traffic data is fusioned with social sensor data from Twitter to check the plausibility of events. Studies in the area of general mobility aim to derive characteristic motion pattern from a single user and a crowd from Twitter. Wakamiya and Lee (2012) extract mobility patterns over Japan by spatial partitioning tweets (e.g. using administrative areas, a grid and voronoi clusters). Ferrari et al. (2011) and Fuchs et al. (2013) detect urban patterns in the US by spatio-temporally analyzing tweet and user activities including semantic topic modeling. Yuan et al. (2013) complement the approach analyzing location and user activity and predicting mobility pattern. Terms appearing in Twitter are clustered, classified and analyzed concerning their spatial distribution by Andrienko and Andrienko (2013) in order to detect spatial behaviors. Sadilek et al. (2013) extract spatio-temporal motion of user trajectories in Twitter.

3.4.2 Location inference

Location inference describes the process of retrieving direct or indirect geolocation information from Twitter either using provided metadata (user profile) or the semantic tweet content. Ribeiro et al. (2012) focus on enriching geolocation and georeferenced tweets by inferring location from user profiles and their social network (friends). Finin et al. (2010) construct a

Named-entity recognition from Twitter to build up a crowdsourced natural language processing. A language-based model to predict user locations is introduced by Kinsella et al. (2011). Hecht et al. (2011) evaluate semantic georeferencing methods from user profiles in Twitter comparing term frequencies (tf) and Naive Bayesian Classifier. Chu et al. (2010) and Hong et al. (2012) develop a location-aware topic modeling integrating a Naive Bayes classifier to correlate relationships between location and words. Kulshrestha and Gummadi (2012) infer user geolocation by correlating user origin and Twitter population. Li et al. (2011) propose an estimation ranking method to predict POI tags on tweets. Lee and Hwang (2012) spatially correlate indirectly inferred geolocation through tweet content and user profile with GPS coordinates from the geotag. Gonzalez and Chen (2012) as well as Hiruta et al. (2012) further adapt the approach realizing a location inference system using profile location and semantic classified tweets. Watanabe et al. (2011) focus on a tweet content analysis by creating term association rules to automatically geotag non-georeferenced Twitter data for local events. Dalvi et al. (2012) geolocate users by matching posted tweets containing indirect spatial information to real world spatial objects.

3.4.3 Social network analysis

Social network analysis intends to investigate characteristics of individual users within a network and their social relationships towards each other. The majority of reviewed papers analyzed textual information from tweet posts and additional metadata (e.g. user profile, follower, following, retweet). According to Hong et al. (2011) conducting a large scale linguistic Twitter analysis, 51% of all posted Twitter tweets are in English. Pennacchiotti and Popescu (2010) classify linguistic features with LDA topic modeling to detect political affiliation, ethnicity identification and affinity for a particular business for each Twitter user. Wu et al. (2011) categorize users and their affinity for different news topics having different characteristic lifespans of content. Takhteyev et al. (2012) geo-reference users and detect individual spoken languages to assess social ties in Twitter with a correlation and regression analysis and airline flight data as a ground truth. Cha et al. (2010) measure individual user influences on topics by analyzing user tweet and retweet behavior. Weng et al. (2010) also study on estimating influence of distinct user calculating and ranking topic similarities with LDA and the relationship structure (friend, follower etc.) for each user. Krishnamurthy and Arlitt (2006) and Yardi and Boyd (2010) identify classes of Twitter users and their behaviors looking into typical social network conversations by analyzing retweets. Cranshaw et al. (2012) examine Foursquare data posted through Twitter by employing a spectral clustering algorithm to discover characteristic neighborhoods showing a spatial and social proximity.

A subfield of social network analysis and computational linguistics are sentiment and emotion analysis for Twitter applying methods of NLP. Go et al. (2009) conduct a Twitter sentiment analysis using SVM classification, Naive Bayes and Maximum Entropy machine learning technologies. Wang et al. (2012) have a system for real-time Twitter Sentiment Analysis during the US election integrating NLP and tf-idf. Quercia et al. (2012) classify sentiments and topics also by extracting emotion words with NLP and weighs the effect on social ties among user.

4 Discussion

During the paper-screening process, an increasing number of publications concerning research on Twitter between 2005 and 2013 can be postulated. This effect over time is not surprising given the fact Twitter received increased attention by users, which is also mirrored in the growing attention Twitter received by researchers. However, when focusing on the amount of published papers over time from different electronic databases selected during the review, we can discern a broadening of the range of Twitter-relevant articles. From 2005 to 2010 most selected studies have been published within ACM. From 2010 onwards more reviewed studies have been produced by a greater variety of publishers (IEEE, Elsevier, Springer). Therefore, research has intensified and spread over further research domains, since the targeted audience of every electronic database is different.

Most of the reviewed studies dealing with spatiotemporal Twitter analysis (43%) processed textual information from tweets by applying keyword-based filtering techniques. Limitations of Twitter analysis mentioned in the reviewed studies are mainly related to the uncertainty and sparseness of the dataset, making a validation and comparison with reference data difficult. Other peculiarities have been faced due to the limitations of the Twitter API query (e.g. size of bounding box, where to retrieve data) and maximum character limits of tweet posts.

Concluding the results from RQ1, most of the literature concerning Location-Based Social Networks and Twitter originates from the field of computer and information sciences (76%), which have been the main academic disciplines to publish papers about Twitter between 2005 and 2011. More input from other disciplines would broaden the existing studies and might lead to new research directions. Research groups already working in the field of Location-Based Social Networks would directly benefit from new interdisciplinary methods and could further advance their own research. From 2011 onwards, other disciplines like earth/geosciences and social sciences also conducted and published research papers regarding the spatiotemporal analysis of Twitter. One explanation can be seen in the increasing penetration rate and use of social networks by people who are exchanging more and more locational information supported by a growing availability of mobile devices equipped with GPS. Within the field of geosciences, for example, this development enables the possibility of utilizing 'Citizens as Sensors' (Goodchild 2007) for a (near) real-time detection and geolocation of natural hazards. In this manner, reviewed studies and their application domains have shown that the study of geographical processes by using spatiotemporal information from location-based social networks represents a promising yet underexplored field for GIScience researchers.

Summarizing the results of reviewed studies (Table 3), georeferenced tweets provided accurate location information for all application domains. However disaster management has been the primarily identified application (RQ2) of Twitter data usage. Within this application domain, study outcomes have demonstrated a high spatiotemporal reliability and usefulness of tweets. Earthquake detection from Twitter is one successful example in a number of reviewed studies where disaster events have been localized in a real-time manner, showing a high correlation in comparison with official earthquake sensor data. A similar outcome can be stated within the application of disease and health management. Tweets indicating disease incidents have shown a similar spatiotemporal distribution in comparison with official reports. These studies provide a first ground truth on how representative and trustworthy tweets for different application domains are. The additional value of this emerging, inexpensive and potentially widespread data in comparison to traditionally acquired data is their high spatiotemporal resolution. This opens up the possibility of designing early-warning systems that detect spatial patterns and events in a (near) real-time manner, and thus may add to or validate existing information sources. These study methods could also be applied in the area of event detection for traffic and human mobility related applications where research has only been conducted in a few cases. Considering the previous studies, more research on spatiotemporal analysis of events in the area of traffic management might show a similar outcome.

Research on social network analysis conducted in 14% of all reviewed studies has been able to investigate the characteristics of individual users within a network and study their social relationships. The investigation of social ties which also considers spatial distributions could potentially be a benefit for GIScience researchers to spatiotemporally analyze collective social activities in order to understand geographical processes. Indeed, none of the reviewed studies related to GIScience have been found analyzing location-based social networks for applications related to urban planning and management

Reviewed studies dealing with location inference from social networks were able to extract and predict locations of users and places (e.g. points of interest) from Twitter using all available information. These results could be used to increase the precision and accuracy of locations within applications for event detection, by additionally analyzing textual information from tweets as well as metadata (e.g. user profiles).

Looking through all applications, Twitter data has been obtained mainly for the US. Twitter data for Brazil, for instance, has only been analyzed for two use cases, although the Twitter penetration rate for Brazil is one of the highest (Graham and Stephens 2012). The available research consequently does not match up with the quantitative geographical distribution of Twitter usage and indicates the need of future studies to span a wider geographic coverage. This can be a potential bias factor since research results might have a different outcome in other study regions. When focusing on the ratio between the active Twitter user and the general population, there is a mismatch between population and sampling frame. The effect known as sampling bias might lead to exclusion or under/over representation of certain population groups.

Disaster management has been one of the main identified application domains researched predominantly by scientists from the information science field followed by the earth and geosciences (RQ1 and RQ2). Many studies originating from the earth/geoscience disciplines are mainly dealing with emergency and disaster management.

Since there is a strong concentration of studies in the area of event detection, specific application domains like disaster management could benefit from this methodological knowledge during the impact analysis of disasters in order to strengthen situation awareness and improve emergency response, especially in areas with a lower availability of high-resolution official data sources such as in situ sensors.

The majority of reviewed studies (71%) from computer science faculties have no specific application context and are, unsurprisingly, principally focused on developing system architectures and investigating scientific methods to improve technological implementations (RQ1 and RQ3). In contrast, publications from the field of information science are leading the research on event detection by primarily applying methods to extract textual information from tweets.

Focusing on methods (RQ3), one identified research gap from a GIScience perspective is the lack of common methods (e.g. applying spatial data mining techniques), in order to adapt to new data types. Georeferenced social media feeds are one example of these new uncertain and sparse data sources. Density-based spatial clustering techniques have been the main applied spatial methods of reviewed studies. Point-based observations are clustered based on distance measures. However, this highly complex and spatiotemporal uncertain information from location-based social networks causes difficulties in finding appropriate parameter values of distance measure thresholds. The parameter inference of existing methods is affected by influences due to different point densities and geographic scale effects. Current methods might not sufficiently incorporate these real world geographical characteristics of datasets (Miller and Goodchild 2015). If one is investigating a spatial phenomenon at a wrongly adjusted analysis scale, the analyst misses out the essential information (i.e. spatial variation). Thus, these issues are crucial for the exploration of latent pattern and the ability to sense geographical processes from Twitter and are classic geographic topics, which offer a great potential for future GIScience studies.

Furthermore, event detection has been the predominant methodological research area for more than 46% of papers. In contrast, only 20% of the reviewed papers propose a system architecture which could be a potential service application, e.g. for supporting stakeholders during the pre-impact of an extreme event or during an emergency response. Since in many cases information about the occurrence of the event can be considered as given (e.g. in some disaster events), it seems that there is currently an overly strong concentration of studies in event detection, without resorting to other information sources (e.g. authoritative data such as those from remote sensing, in situ sensors, official organizations). Thus, improved spatiotemporal analysis methods for extracting useful and more detailed information about events from Twitter data that leverages existing geoinformation sources (e.g. Herfort et al. 2014) are an important topic to be addressed by future work in this area.

Most of the reviewed studies (75%) dealing with spatiotemporal Twitter analysis processed textual information from tweets by manually applying keyword-based filtering techniques. More use of computer linguistic approaches with advanced methods to infer textual information from tweets, combined with methods of spatiotemporal analysis, might provide further insights since the number of available studies from computer linguistic disciplines using spatiotemporal information have been small (RQ1 and RQ3). At the same time, a changing temporal pattern over the last few years from the exclusive use of semantic information to a focus on spatial aspects of Twitter data has been revealed (Figure 8), which underlines the possibility of combining methodological knowledge of processing semantic and spatiotemporal information. Within the application of social network analysis, semantic information and user metadata (user profile, follower/following information) from social networks have been primarily used to study social relationships (RQ2 and RQ3). These information layers have also been mainly used to conduct sentiment and emotion analysis. Using the spatial information of geotagged tweets during sentiment and emotion analysis might lead to new insights such as how people spatially perceive their surroundings (e.g. urban emotions). Reviewed studies in the area of disaster management also focused on analyzing posted website links (url) through Twitter in order to track what and how information regarding disaster events disseminates in social networks. This knowledge could also be beneficial during other events like diseases or mobility-related incidents, providing stakeholders with insights and strategies on how to publish and manage information.

In summary, GIScience contributions, especially regarding the integration of spatial methods, have been rare and underrepresented during the literature review. Although 43% percent of papers work with spatial data, only 7% of all reviewed papers have been written by those from a geosciences background (RQ1 and RQ3). The location component of Twitter has been considered in several studies. However, certain academic disciplines and application domains are over- and under-represented when reviewing the current state of research and this study has revealed current gaps and areas for future work. These are from a GIScience perspective:

1. The lack of common methods for spatial analysis in order to adapt to new uncertain data types of location-based social networks such as Twitter.
2. The current spatial methods only marginally incorporate geographic scale effects within the spatial analysis of Twitter data.
3. The lack of combination of different methods within Twitter analysis (e.g. social network analysis, semantic analysis, spatiotemporal analysis), in order to better utilize all available semantic and spatiotemporal information layers.
4. The lack of methods that leverage other data sources not only as reference data, but also for data fusion and improving information extraction in the analysis of Twitter data.

In this manner, conducting a systematic literature review is an efficient way to select the best available research and facilitates research approaches by identifying current existing research gaps and study limitations. The outcome of this study provides an overview on the state of research with new insights into identified spatiotemporal applications and methods which are potentially applicable to other location-based social networks and VGI platforms showing similar data characteristics.

Finally, the conducted review has some limitations. Looking through digital libraries (Section 2) which might use different non-transparent search algorithms might generate selection bias, especially when combining search results. Another possible selection bias occurs when non-English citations are excluded. Since the state of research regarding the spatiotemporal analyses of Twitter is reviewed, we might create a sampling bias which could lead to exclusion or under/over representation of certain research studies. Thus, specific problems of research on LBSN might only occur within certain sampling frames chosen by the researcher. Depending on the Twitter information and analysis the researchers are focused on (e.g. only georeferenced tweets), unrepresentative subsets and different sample sizes from the whole amount of tweets might be generated. Moreover, results from the systematic literature review strongly depend on the input data. Therefore a limiting factor of this systematic literature review was crawl and search limitations of electronic databases, and research papers not being fully accessible.

Another key limitation is that primary studies are very heterogeneous concerning methods and applications, because used terms can be unclear in the varying academic disciplines. The search term "social media" is one example which was excluded, since search results during the metadata analysis have shown that no relevant research papers with specific methods and use cases were extracted. Keywords arbitrarily defined by researchers can be an issue since these buzzwords (e.g. social media and big data) appear and disappear during temporal and the technological development (Levy and Ellis 2006). Therefore the underlying methodologies might be subject to a more static development, but difficult to assess quantitatively with a systematic literature review. Another limiting aspect is the initially defined search terms during the keyword-based search, which might be subject to bias, as terminology could be influenced by academic discipline and background.

To assist the selection process a backward reference search has been performed within the qualitative review. Implementing an automatic citation search approach during the quantitative review, however, was not possible at this stage, due to the high amount of primarily included papers and the fact that metadata of research papers currently does not contain machine-readable information concerning used references.

When investigating academic disciplines mainly researching on Twitter (Section 3.1) during the review analysis (Section 3), we extracted disciplines according to the department or affiliated research institute. However, this procedure does not take into consideration authors working at a certain department but having a different academic background.

5 Conclusions

This article has presented a systematic literature review on the state of research concerning methodologies, applications and use cases of Twitter as a Location-Based Social Network. The proposed systematic literature review method considers and combines search results from multiple heterogeneous digital libraries and allows an effective reproducible assessment of relevant research studies. Together with the implementation of an iterative keyword-based search considering metadata analysis results, we were able to minimize bias during the overall review process. A combined approach of quantitative and qualitative review methods decreases the percentage of possible papers which have not been detected at all. One of the main advantages of the advanced systematic literature review, when compared with non-systematic reviews, is the degree of confidence that the available literature has been exhaustively and systematically searched. Non-systematic literature reviews are biased by the impact of human subjectivity, selecting relevant research papers in a non-reproducible, arbitrary manner. Papers identified in our systematic literature review have been selected from multiple electronic libraries and provide a much broader multidisciplinary perspective.

Finally, we were able to answer our initial research questions (Sections 3.1–3.3) and provide new statistics-based insights for Twitter as a Location-Based Social Network. In this manner, we have shown the need for new research contributions from yet underrepresented disciplines within this systematic literature review and hope to further encourage and foster new research especially from the GIScience field. GIScience can contribute essential research methods in order to advance the research of Location-Based Social Networks by further integrating methods of spatial analysis. One GIScience research objective should be to develop novel methods and approaches towards the spatiotemporal analysis and exploration of social-media data by leveraging existing geographic knowledge. This research could provide stakeholders with near-real-time information and could lead to new insights by analyzing geographic and social aspects of Twitter.

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