Faculty of Environmental Sciences Department of Geosciences Institute of Cartography

Subjective Value Assessment Based on Emojis for Applications in Landscape and Urban Planning

submitted by **Elifcan Özyıldırım** born on 29.04.1993 in Edirne, Turkey

submitted for the academic degree of
Master of Science (M.Sc.)

Submission on 10/09/2019

Supervisors Prof. Dipl.-Phys. Dr.-Ing. habil. Dirk Burghardt
Institute of Cartography, Dresden University of Technology

Dr.-Ing. Eva Hauthal
Institute of Cartography, Dresden University of Technology

Reviewer Dr. Evangelia Drakou
Department of Geo-information Processing,
University of Twente

Statement of Authorship

Herewith I declare that I am the sole author of the thesis named

„ Subjective Value Assessment Based on Emojis

for Applications in Landscape and Urban Planning "

which has been submitted to the thesis assessment board today.

I have fully referenced the ideas and work of others, whether published or unpublished. Literal or analogous citations are clearly marked as such.

Dresden, 10/09/2019 Signature

Acknowledgements

I would like to express my gratitude to a few people who supported me in my life and in my final year of graduation.

I sincerely thank my supervisors Dr. Eva Hauthal and to Prof. Dr. -Ing Dirk Burghardt for their time and feedback and support me with my ideas and work. Thanks to Dr. Evangelia Drakou for her feedback and ideas.

My profound thanks to Dr.-Ing. Alexander Dunkel for his support, encourage and ideas, especially for guiding me in such an interesting topic.

I wish to express my deepest gratitude to M.Sc. Juliane Cron, the person who made me like maps! I will always be grateful to her for not letting us alone in a foreign country.

My dear classmates, Agnieszka, Cynthia, Iñigo, Kevin, Marko, Rima ,Victoria, Wouter, Zarina and all others who were the sweetest and friendliest people I have ever met. Even though we were apart for the last months, it was priceless having them. I will never forget our journey.

I would like to thank my chosen family for being there for me. Thanks to Ceren, who gave me rainbows after every rain; to Ece, who held my hands and never left; to Seda, who let me be myself; to Gülce, who truly believed in me.

I want to express my deepest appreciation to my lovely sister and my parents. My appreciation is beyond letters. I could not have done it without them. Lastly, thanks to my dear grandmother, for all the love. No doubt, she would be proud of me if she were still with us.

Abstract

Emojis are digital images used to express ideas, emotions, activities and situations. Emoji usage in social media has been widely accepted by users and has generated a new and interesting practice in research. At the same time, use of Location-Based Social Media (LBSM) has become popular in a range of fields, including urban planning studies. Examining emojis in social media data is compelling because users utilise emojis to indicate their feelings, their activities and their locations. Geolocated social media data can be used to explore and understand the city by finding an approach to transform this data into information.

This research discussed the capacity of using emojis in social media data for urban and landscape planning applications. The first part of the methodology was creating an emoji taxonomy. Emojis were assigned to three different categories: *Objects, activities* and *sentiments*. This was made considering the capability of emojis representing one of these categories and essential points to know for an urban planner and decision-maker. The posts in LBSM data geolocated in Dresden, Saxony in Germany were also categorised to be visualised based on the generated emoji taxonomy. The posts were categorised according to the emojis contained within. Whichever category of emoji in it, the post was assigned to that category.

An interactive geovisualisation method was adopted, and a web map was built to explore the LBSM data in Dresden together with the categories (https://elifcanozyildirim.shinyapps.io/mapemoji/). After the categorisation and geovisualisation process, the functionality of exploiting emoji usage in LBSM for urban and landscape applications was assessed with the case scenarios. It was proven that emojis are used in accordance with the locations and activities. Therefore, the use of emoji taxonomy and the geovisualisation have been shown to be advantageous to use as an information source. In addition, emoji usage in social media can aid to assess subjective values, analyse different activity types patterns, landmarks, temporal changes and sentiments in the city. This study strengthened the position that LBSM is a useful resource for the urban planning profession. However, the following shortcomings were also identified: Emoji use differs between users, the post context and emoji selection may vary from one another, users tend to look positive in social media and the locations of posts may not be correct. Therefore, this research concluded that proper care should be taken when taking emoji usage in social media as a source of information.

Contents

Figures

Tables

Graphs

List of Abbreviations

GIS	Geographic Information Systems
LBS	Location-Based Services
LBSM	Location-Based Social Media
NLP	Natural Language Processing
SNS	Social Networks Sites
UI	User Interface
VGI	Volunteered Geographic Information

1. Introduction

This chapter will clarify the motivation behind doing this research, research objectives and research questions.

1.1. Thesis Outline

The thesis was held in five sections. In the Introduction, the motivation and statement of the problem together with the research objectives and questions will be given. The second chapter will outline the key concepts like social media, using location-based social media for urban fields and the related works in the literature. The third part consists of the methodology and it was given together with the results; the reader will here discover the methodological approach in detail. Use case scenarios and the assessment of case scenarios were given under section four. Lastly, the contributions of this paper to current research, limitations and future work will be discussed.

1.2. Motivation and Problem Statement

Smartphones are now an essential part of our daily lives, and as a result of affordable smartphones and data plans, the number of social media users on Instagram, Twitter, Facebook and many others have reached to billions (Frias-Martinez *et al.*, 2012). Furthermore, social media offers the possibility to share ideas, emotions, upload visuals, making a comment on the places they have been or an ongoing event. Social media users share their satisfaction degree, emotions or critiques. Adoption of new technologies has brought new ways of discovering human dynamics through generated data. Social media messages that contain spatial information, which is called as Location-Based Social Media (LBSM) has become a unique data source that allows researchers, planners and scientists to analyse, understand and map the relationship between people and places.

The responsibilities of urban planners are to observe, gather information, state the problems, bring knowledge and solutions into the decision-making process for a better future of cities and societies (Hall and Tewdwr-Jones, 2010). The information can be gathered through observations, surveys, questionnaires or direct meetings. However, these methods have certain limitations like the costs of running questionnaires and restricted number of people that can join the survey. Meetings and questionnaires made with a limited number of people cannot bring a broad perspective for controversial issues. As an alternative, Geographic Information Systems (GIS) can provide information about the land, yet it fails to bring knowledge about citizens, their daily activities and the level of wellbeing. Utilising LBSM data to retrieve information differs from approaches mentioned above because the insight is ascertained directly from the actions of people without questioning. A city is not only made of streets, parks and buildings but the community and their social practices. Different from past, we do not only map the buildings and cities, but we can now map abstract things like human geography (Stefanidis, Crooks and Radzikowski, 2013). The association between the physical environment, social practice and perception of the place have always been a tricky field (Hutchison, 2014). LBSM data has the potential to assist in exploring and visualising abstract concepts like sentiments, opinions and the relationship between the spatial areas and humans.

The variety of individuals in social media, so the information that can be extracted from this data is relatively rich. Scholars have adopted LBSM data as an information source in their studies; to characterise the land use and landmarks (Frias-Martinez *et al.*, 2012), to understand the feelings and perception of citizens in the city (Williams, 2012), to identify sentiments and ideas about urban planning decisions (López-Ornelas, Abascal-Mena and Zepeda-Hernández, 2017), to map mobility patterns and human activities in urban areas (Hasan, Zhan and Ukkusuri, 2013). The scholars advocated the fact that social media data is useful and valuable to explore urban areas.

Meanwhile, sentiment analysis and opinion mining have gained much attention, and social media data has become a source for these tasks. Through Natural Language Processing (NLP), sentiments and reactions have been extracted from social media. Scholars pointed out the potential of making use of emojis, arguing that emojis are strong indicators of feelings (Hu *et al.*, 2013; Fernández-Gavilanes *et al.*, 2018). The use of emojis has become widespread and through emojis, it is possible to research and compare user behaviours and preferences across nations and cultures (Lu *et al.*, 2016).

The inspiration behind this research was making use of emojis for urban and landscape planning applications. Similar to previous investigations, LBSM data was used to explore the city, but unlike earlier researches, it was made based upon emoji usage. This study progresses in four steps; (1) making a taxonomy of emojis, (2) analysing emoji usage in social media data, (3) creating proper visualisations for a better understanding of the public dimension in urban areas, (4) deliberating the results over geovisualisation for city of Dresden, in Saxony, Germany. Following chapters will discuss the advantages and disadvantages of analysing emoji use in social media data for urban planning.

1.3. Research Objectives and Research Questions

This research principally aims to portray that, proper analysis and geovisualisation of spaces based on emoji usage would aid not only to get a unique idea about the perception of the city and the characteristics of the places but also would help to shape planning decisions and evaluate them in the long term. Objectives of this study are as follows:

> ***RO1:*** *Finding suitable approaches for filtering emojis and assigning the related emojis into three categories; objects, activities, sentiments.*
>
> ***RO2:*** *Developing an informative geovisualisation of LBSM posts based on the use of emojis in order to use it as an information source in urban and landscape planning.*
>
> ***RO3:*** *Discussing the usability and limitations of analysing emojis in social media with a case scenario in, e.g. parks, a public square, a shopping street, a neighbourhood.*

In this study, a methodology that focuses on clarifying the following research questions was adopted. These questions were defined as the following:

> ***RQ1:*** *How to classify emojis as objects, activities, sentiments in a way that it relates to urban planning and helps to outline the features of the environments and the perception of people about these places?*

RQ2: *How to visualise social media posts geolocated in Dresden based on the emojis and taxonomy, so that it becomes an information resource for decision-makers and urban planners?*

RQ3: *What are the possible benefits of analysing emojis in geolocated social media posts for urban and landscape planning applications to analyse a city through citizens' eyes?*

2. Theoretical Background and Related Work

The study subject was chosen in conformity with relevant findings of researchers and promising future of investigating emojis in geolocated social media posts. First and foremost, it is crucial to familiarise with the framework and related concepts. This chapter will present the key concepts and relevant studies.

2.1. Social Media

"Social media is increasingly becoming part of our everyday lives." stated Williams (2012). Kaplan and Haenlein (2010) defined social media as web-based applications which produce and exchange user-generated content. Social media gives the users a voice, erases the line between media and audience and supports the growth of groups with similar interest (Kaplan and Haenlein, 2010). Williams (2012) stated that users do not register only their locations, but also their activities and their opinions. Social media has been a communication tool, now it has become a data resource for numerous purposes too, like evaluating customer satisfaction, understanding opinions and sentiments, tracking trends and observing reactions to events.

2.1.1. Location-Based Social Media Data

Location-Based Services (LBS) are services that integrate a mobile device's position with another kind of information to provide better service to the user (Schiller and Voisard, 2004). Several industries benefit from LBS, such as tourism, health, entertainment, and security. Consequently, LBS have implemented the technology for social media users to share their location from their social media networks. Social media connects people, moreover, lets both users and researchers comprehend, discover and document the information users register. Economists, politics, governments, urban planners, commercial organisations, along with many other organisations, have taken advantage of LBSM for analysis and development of plans.

Social media data with spatial content offers a more comprehensive material when it comes to the understanding of socio-spatial dynamics. The users share their knowledge, but this should not be confused with Goodchild (2007)'s term "volunteered geography". Volunteered Geographic Information (VGI) refers to the user-generated content (Goodchild, 2007). Flickr, OpenStreetMap, Wikimapia are some of the examples where users voluntarily provide information about spatial areas. Geolocated social media posts create a kind of VGI. However, they are not precisely VGI, because users do not volunteer for giving their knowledge about a place, but the information they provide can be still utilised for other objectives. Scholars defined this as ambient geospatial information, and the emergence of this kind of information represents the second evolution of geospatial data, followed by VGI (Stefanidis, Crooks and Radzikowski, 2013).

2.1.2. Geovisualisation of LBSM

Day by day, the amount of available data and consequently, the degree of data complexity is increasing. One of the biggest challenges for information science is finding ways to transform the data into information and ultimately into knowledge. Large volume, difficulty in defining reliable and unreliable information and limited tools to extract meaningful information from social media make the use of data challenging (MacEachren *et al.*, 2011). This problem can be overcome by effective visualisation methods.

Visualisation refers to the conversion of raw data into displayable images for turning information into a way that human perception can capture (Haber and Mcnabb, 1990). Using graphs, charts, maps are more descriptive and more explicit than unstructured datasets and texts. Geovisualisation, on the other hand, was defined as a mix of approach to provide theory, methods and tools for exploring, analysing and representing geospatial data (MacEachren and Kraak, 2008). LBSM data has a complex and multidimensional structure, and dynamic geovisualisation methods are necessary to assist the viewer in understanding the data.

Static visualisations can present only limited dimensions of the data, but interactive visualisations can empower people to explore data themselves, and represent multidimensional datasets (Murray, 2013). Creative and dynamic cartographic representations are developing as cartographers exploited the advanced technologies from other disciplines like computer sciences (Rhyne, MacEachren and Dykes, 2006). Kiousis (2002) defined interactivity as the degree to which communication technology can generate a facilitated environment where users can interact with systems. Advanced interactive techniques of geovisualisation are now regarded as helpful for discovery and for presenting data (Dykes, MacEachren and Kraak, 2005). They are advantageous as they allow exploration through interaction.

Analysing social media data can sound impractical because of its complexity, but interactive visual representations facilitate interpreting this kind of data (Bal, 2008). Fan and Gordon (2014) divided social media analytics into three steps: capture, understand and present. Capturing is related to finding the relevant social media data from different sources, understanding is removing the low-quality data and applying analytics methods to understand it, and lastly presenting stage answers to the need of turning these findings into meaningful displays (Fan and Gordon, 2014).

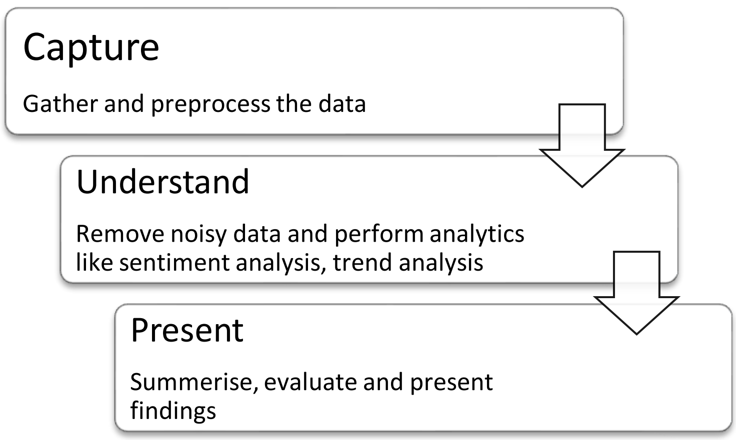


Figure 1. Social Media Analytics Process, Adapted from "The Power of Social Media Analytics" (Fan and Gordon, 2014)

At the presenting stage, where the findings should be displayed in meaningful ways, using interaction would bring successful solutions and overcome the complexity of social media data. It would encourage engagement and allow the user to explore the data according to the area of interest. An interactive geovisualisation of LBSM data with filtering features can assist urban planners in understanding separate pieces of information in one piece.

2.2. LBSM in Urban Studies

When geolocated social media data is turned into actionable insights, it can provide unique information to be used in urban planning applications. This chapter will present the related works and discuss the features of LBSM.

2.2.1 The Utilisation of Social Media Data in Urban Planning and Related Researches

Urban planning is a profession and interdisciplinary field which focuses on design, regulation, functions and social impacts of the space which brings engineering, architecture, social and political disciplines together (Fainstein, 2016). The main concern of planning is to understand and regulate the connection between spaces and people, not only by building and changing environments but also by keeping in mind that planning and design are for people.

An interesting chance has arisen, to create unique methods to conceive and visualise the dynamics, structure, and personality of a town (Tasse and Hong, 2014). Urban planners require significant amounts of data for better and successful planning applications. Any information concerning city dynamics is supportive for a planner to understand and analyse the town.

The public dimension of a city cannot be ignored nor underestimated in urban planning. Lynch (1981) stated this dimension as "sense", as a connection between cognition and physical environment, and reflects the way people sense the environment in their minds. He criticised planning approaches regarding "legibility"; a city is not just a thing by itself, but how its inhabitants perceive it (Lynch, 1981). Analysing a city using geolocated social media posts provides different perspectives comparing to traditional examinations, especially when observing intangible urban phenomenon like the urban life, experiences and the use of the city.

Researches utilised social media to study the perception of citizens towards a city. In the project "Here Now! Social Media and the Psychological City", the expert investigated a range of socio-economic classes by analysing Facebook and Foursquare check-in locations (Williams, 2012). The researcher generated a cognitive map of the city, demonstrating the collective psychology of social media users, as shown in Figure 2 (Williams, 2012). After investigation and visualisation process, Williams (2012) concluded that geo-locative social media data is informative to explore a city through the inhabitants' eyes, without conducting surveys or using governmental datasets.

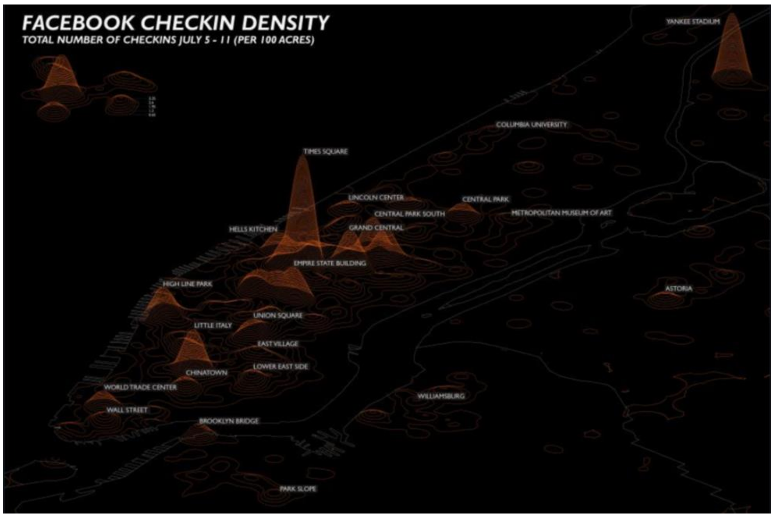


Figure 2. Geovisualisation of Facebook Check-in Density (Williams, 2012)

Cartographers and urban planners tried to extract information about the socio-economic status of the cities from LBSM. Quercia and colleagues (2012) argued that visualising emotional state of residents is a way to map their socio-economic situation. They conducted a case study in London: They performed sentiment analysis using Twitter data and explored the association between sentiments and socio-economic well-being (Figure 3). Although they encountered demographic biases in the data, regarding the age intervals and average income, they uncovered a correlation between sentiments and well-being of communities (Quercia *et al.*, 2012).

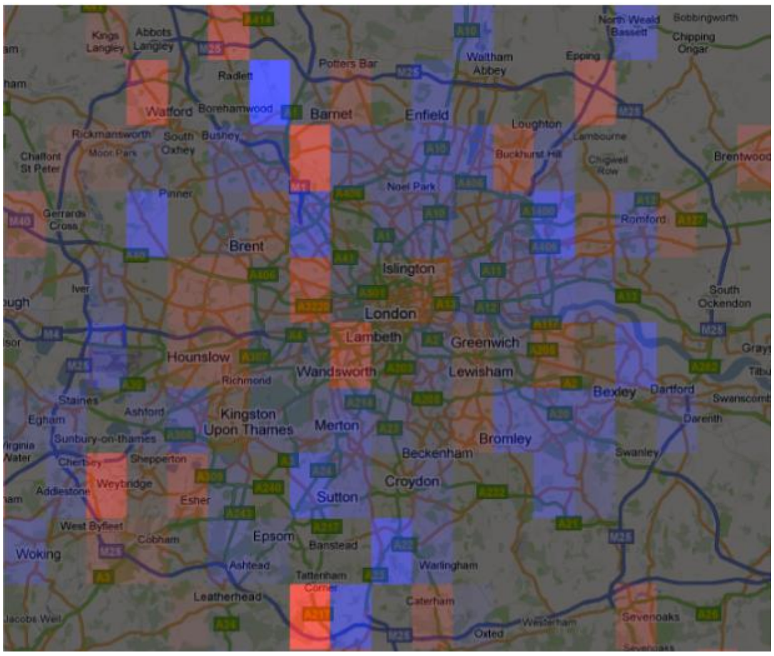


Figure 3. Mapping “Gross Community Happiness” in Greater London, blue colours represent unhappy, and red colours represent happy sentiments (Quercia *et al.*,2012)

Similarly, a study used geolocated Twitter and Foursquare data and determined neighbourhoods using spatial clustering techniques, proving that neighbourhoods which are more active in social media, tend to have better incomes. They aimed to understand the dynamics of districts and create a source of information for future urban development decisions (Anselin and Williams, 2015).

LBSM has been analysed to understand other characteristics of a city too; such as understanding activity types and mobility patterns. A study investigated urban human mobility by portraying aggregated and individual activity patterns and visualised as a virtual grid reference city map (shown in Figure 4) (Hasan, Zhan and Ukkusuri, 2013). This study proved that by analysing social media, it is possible to observe the activity and mobility patterns of citizens.

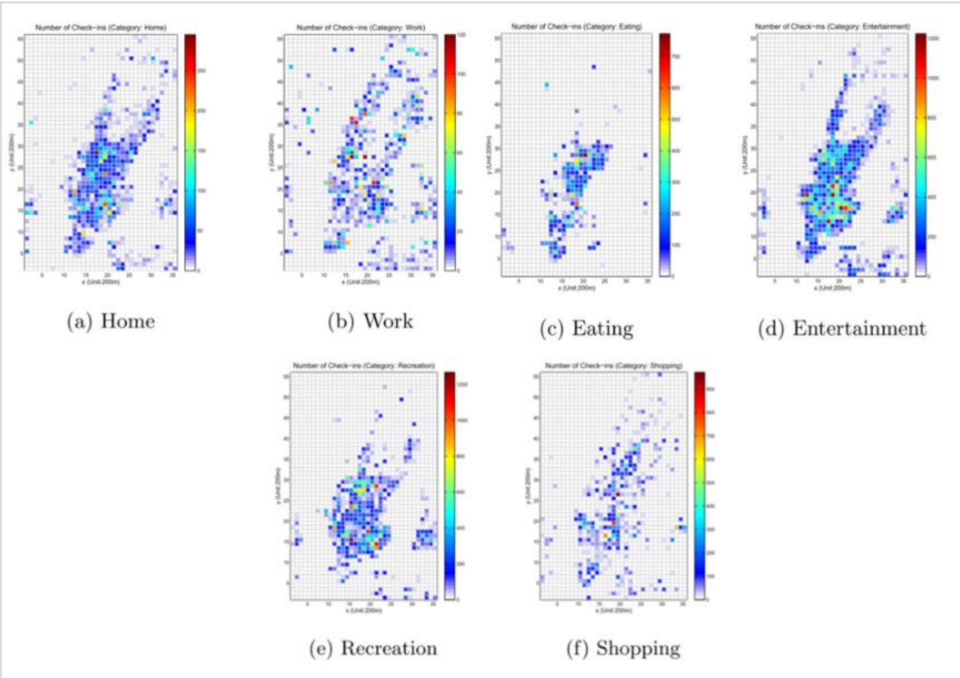


Figure 4. Check-in density for activities in Manhattan Island area in New York City (Hasan, Zhan and Ukkusuri, 2013)

Knowledge about the use of public spaces is crucial for urban planning. Social Networks Sites (SNS) are also strong tools to discover the characteristics of places. One study analysed sports activities using SNS data (Mora *et al.*, 2018). They aggregated the data and visualised it to identify the common places where citizens practice sports. The investigators underlined that knowing the most preferred places is important for urban planners so that the necessary infrastructure developments and citizen-centric policies can be designated (Mora *et al.*, 2018).

Urban planning aims for the wellbeing of citizens by controlling and designing environments, so some of the primary purposes are characterising land use and identifying land-marks (Frias-Martinez *et al.*, 2012). Researchers detected different land uses in Manhattan, New York City utilising Twitter dataset. Using spatial information of tweets, investigators applied an unsupervised neural network to segment the land. Afterwards, they identified urban land uses utilising temporal information and clustered similar activity patterns, as illustrated in Figure 5 (Frias-Martinez *et al.*, 2012). Results show that geolocated information can aid to detect landmarks and land uses.

Figure 5. Geographical representation of Land Use Clusters
From left to right: Business, Leisure/Weekend, Nightlife and Residential (Frias-Martinez *et al.*, 2012)

Dunkel (2015) experimented different visualisation techniques of crowdsourced photo geodata from Flickr to provide aesthetic and perceptual features of landscapes (Figure 6). He argued that these visualisations are helpful to analyse the relative importance of features in an area. Dunkel (2015) stated, the opportunities of using social media data for planners and designers are obvious but successful integration of the results with urban planning process strongly depends on the quality and reliability of the data (Dunkel, 2015).

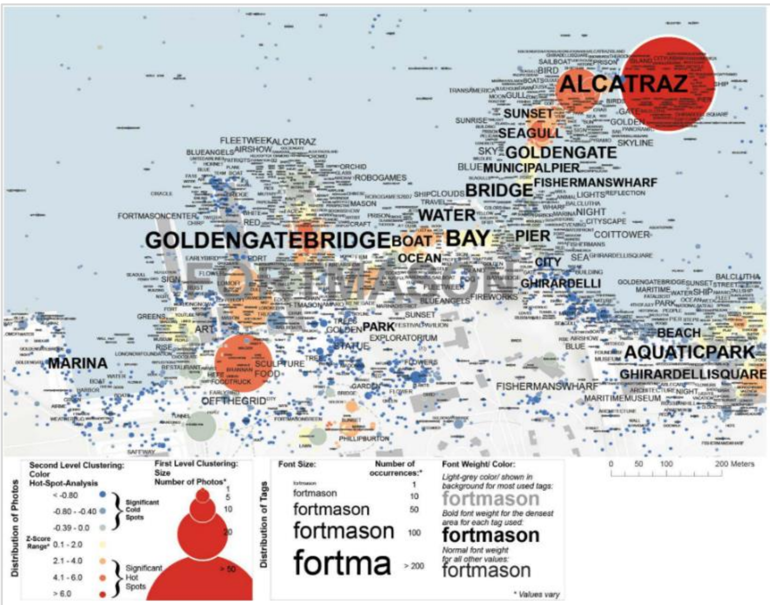


Figure 6. Fort Mason area based on unique tags (Dunkel, 2015)

Crisis management has been vital in decision-making areas, such as regional planning. MacEachren and colleagues (2011) developed a web-based visual analytics application to enable an analysis of Twitter data (Figure 7). They intended to integrate visual methods to place-time-entity framework and assist decision-making process in crisis and predict future states (MacEachren *et al.*, 2011). Similarly, another study analysed microblog posts during the emergency event of Red River Floods in North America using Twitter data that was generated during the flood period (Vieweg *et al.*, 2010). Their purpose was to improve situational awareness for both public and emergency responders by using extracted information from social media data (Vieweg *et al.*, 2010).

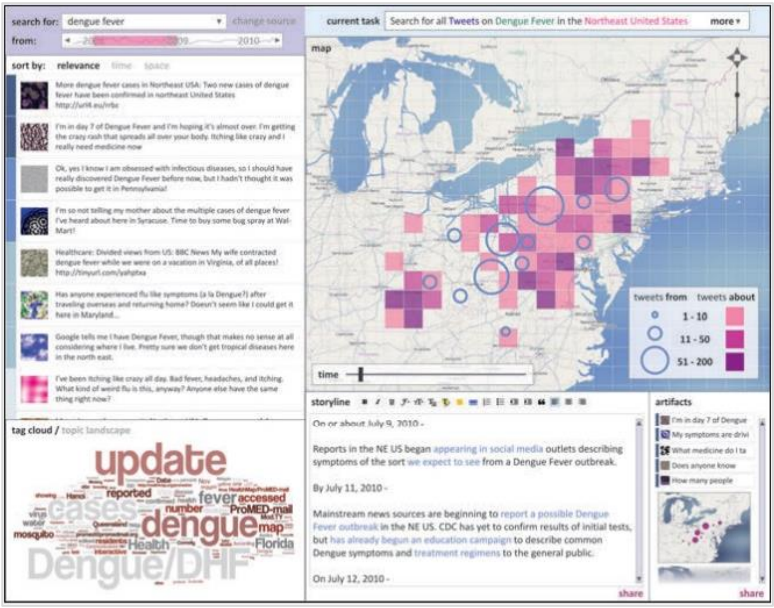


Figure 7. SensePlace2: Geo-Twitter analytics support for situational awareness (MacEachren *et al.*, 2011)

Other study aimed to extract past events from social media data. A visualisation was created to reconstruct past events using activity traces (geo-referenced photos from Flickr and mobile phone calls) by using a combination of tools like interactive geovisualisations, geo-computations, and statistical methods (Andrienko *et al.* 2010). The researchers transformed these activity traces into spatially referenced time series and visualised for a better interpretation. Researchers came to the conclusion that methods for visualising this kind of data should be combined with other interactive visual displays to allow analysis to discover different patterns in data.

Previously mentioned researches indicate that the analysis of urban areas through information collected from LBSM has gained significant attention as a promising technique for applied research. An increasing amount of LBSM data has provided researchers a fresh and important information source to understand the city, citizens, and the relationship between them.

2.2.2. Characteristics of LBSM Data

The amount of data is constantly increasing along with the popularity of the Internet; every activity that relates to the Internet is recorded as data. Economic, physical and social activities that are performed in social networks or on web are recorded as an abundant number of datasets. Data is now large-scaled, less structured, yet is available for things which were hard to observe in the past (Einav and Levin, 2014). On the one hand, LBSM data can now be utilised for a range of fields more effectively, but on the other hand; the data became more complex and ambiguous to explore.

Big data was described with three V's model: "it is high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation" (Gartner Inc., 2013). The potential of data is undeniable, but making sense of this high-volume, high-velocity and high-variety data requires processing, interpreting and both explanatory and exploratory visualisations.

Bias has also been a feature of social media data. One of the challenges that researchers face to use LBSM is the demographic bias, like Quercia and his colleagues (2012) faced in their study, 63% of Twitter users were less than 35 years old and 68% of them had at least $60,000 annual income. Academics proved that social media data was created mostly by users with higher incomes because of mobile phone ownership (Tasse and Hong, 2014). Therefore, LBSM data does not represent the whole population. The model of posts may represent only one specific part of the community rather than an all society. Furthermore, social media activities are much denser in urban areas than in rural areas (Hecht and Stephens, 2014). Scholars must be aware of the biases in models and make clear what exactly the models represent and what they do not represent (Tasse and Hong, 2014). Further limitations will be discussed in Section 5.2, together with the findings of this study.

2.3. Emojis in Social Media

Emoticons are typographic displays, made with using only characters that represent facial expressions, e.g. a smiley face as ":-)" and sad face ":-(". They had become popular in communication apps in the 1990s when the Internet spread around the world. Unlike emoticons, emojis are actual pictures and started to be used in the late '90s. The word emoji consists of two Japanese words; "e" meaning picture + "moji" meaning character. Emojis are smileys or ideograms which are widely used in several devices and applications.

Each year, more emojis were added in Unicode and usage of emojis has progressively expanded. People from different countries, age groups, cultural backgrounds have accepted these pictographs and have utilised them in their text-based communication (Lu *et al.*, 2016). On 5 March 2019, the Unicode Consortium released the latest version Unicode 12.0 (The Unicode Consortium, 2019). Emojis are categorised into eight groups: Smileys & People, Animals & Nature, Food & Drink, Travel & Places, Activities, Objects, Symbols, and Flags ('Emoji Version 11', 2018).

Face to face or phone conversations let people understand each other's mood from vocal clues, but only-text based communications can cause misunderstandings (Subramanian *et al.*, 2019). Emoticons and emojis have the potential to enrich the communication by enhancing the way to show emotional expression. They provide an alternative to visual communication to portray universal emotions, states and activities. Besides, they grant a deeper meaning to the text. One research featured how a smiley face emoticon was processed in the brain, and the investigation established that brains respond to emoticons in similar ways as they respond to faces (Churches *et al.*, 2014). Using emojis is an intention to be clear and sure that message is received in the right way so that the disconnections caused by non-facial communication is prevented (Lebduska, 2014).

The adoption of emojis gives researchers opportunities to conduct studies which had limitations formerly. For example, if there is only the name of a city in a post sent by a user, it does not reveal any ideas or feelings. However, if there is an emoji next to it like "smiling face" (😊), this expresses that the user has positive experiences in this city; or oppositely an "angry face" (😠) indicates negative feelings or experiences (Ayvaz and Shiha, 2017). Lu and colleagues (2016) outlined that researches which were before limited because of language and geographical barriers can be now conducted employing emojis with respect to their widespread acceptance by users across the world. Besides, making use of emojis in social media brings an alternative solution to the researches that have difficulties in conducting user surveys or implementing NLP.

2.3.1. Emojis for Evaluation of Sentiments and Activities

Understanding and analysing what people do, feel and think have an outstanding importance for a diversity of professions. Conducting surveys, questionnaires; detecting emotions from visual-audial tools or behaviours are some of the traditional approaches for collecting sentiments. Sentiment analysis is the study that extracts the attitudes and emotions of people from texts (Liu and Zhang, 2012). It is important to social domains because ideas are the core of human activities and behaviours (Liu, 2012). A wide range of people share their opinions and feelings through channels like social media, and it becomes a noteworthy source to use in sentiment analysis. Running sentiment analysis across social media finds a wide application ranging in predicting results of an election, identifying satisfaction or dissatisfaction of purchaser, approximating stock market prices (Ayvaz and Shiha, 2017). Businesses and organisations value opinions and emotions about the product, event or place, in the interest of improving their services.

Several investigates discussed the approaches and potentials of applying NLP to texts from blogs or SNS. Pang and Lee (2009) aimed to extract emotions and opinions from online review sites, social networking sites, personal blogs and they questioned the disadvantages of running sentiment analysis on these websites. They documented that extracting sentiments from user-generated content is more complex and challenging than applying machine learning algorithms to classic texts because user-generated texts are harder for computers to analyse. The same as other computer systems, intelligence at the human level is deficient in NLP technology (Sattikar and Kulkarni, 2012). Misspelled words, spelling shortcuts and slangs are commonly seen in the Internet world. For those reasons, detecting opinions, moods and emotions by analysing SNS has difficulties.

Emojis can present complex objects or feelings, thanks to their rich visual representation (Lu *et al.* 2016). Scholars exploited emojis even to detect sarcasm in the text and asserted that human thoughts and feelings are best transmitted through emojis because they offer stronger signals than the text (Subramanian *et al.*, 2019). Additionally, interpreting emojis in a dataset is more practical compared to text, because it overcomes the language barriers, as emoji characters are encoded in the Unicode Standard (Lu *et al.*, 2016).

Novak, Smailović, Sluban and Mozetić (2015) created a sentiment lexicon of most frequently used 751 emojis, using approximately 4% of 1.6 million tweets that included emoji. 83 human annotators manually annotated sentiments in each tweet. In the end, academics analysed emojis that occurred in the tweets and assigned a probability of naturality (*p−, p0, p+* for negativity, neutrality, and positivity of the emoji) to each emoji. As a result, most of the emojis were scored as positive. In addition, most of the negative emojis were found as sad faces, but the most commonly used positive emojis were not merely happy faces, but symbols that had no facial expression such as party symbols and hearts. In another investigation, an emoji lexicon from unsupervised sentiment analysis was created, and the use of emojis for sentiment analysis proved to have potential and power (Fernández-Gavilanes *et al.*, 2018).

Ayvaz and Shiha (2017) explored the effect of emojis in NLP and studied the usage of emojis in events related to positive and negative feelings. They chose the events "The New Year's Eve" and "Istanbul Attack". Ayvaz and Shiha firstly applied a sentiment analysis only considering words with the help of a lexicon of words with positive, neutral and negative sentiments. Secondly, the researchers repeated that taking into account the emojis, which were also categorised as positive, neutral and negative. Taking into account the emojis in sentiment analysis, positive results increased, neutral results decreased, and negative results remained almost the same for both events (Figure 8 and Figure 9).

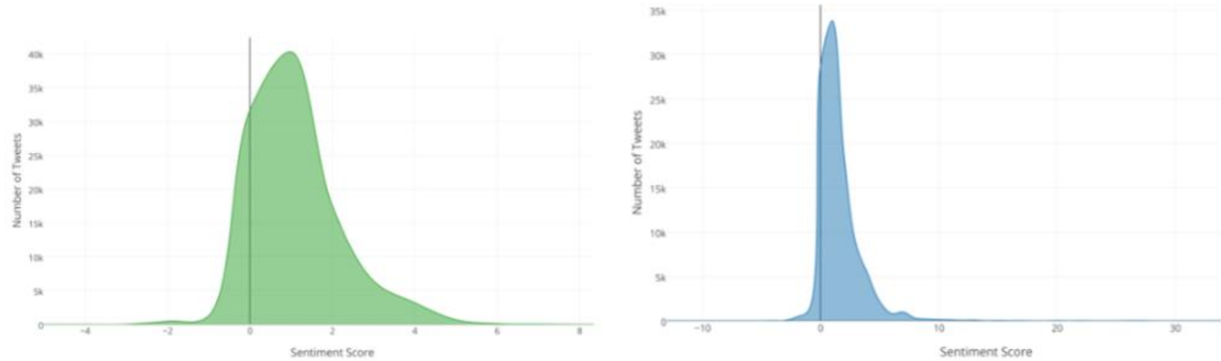


Figure 8. Sentiment scores of "The New Year's Eve" event without the emojis (left) and taking into account the emojis (right) (Ayvaz and Shiha, 2017)

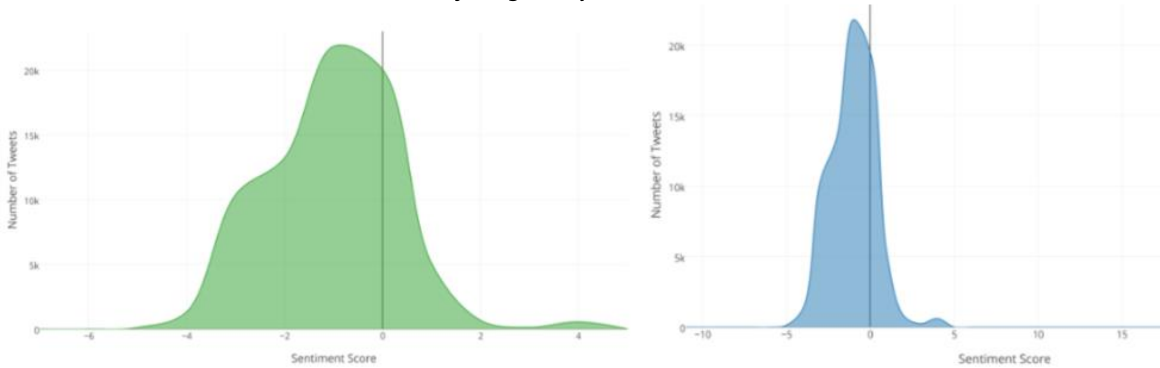


Figure 9. Sentiment scores of "Istanbul Attack" event without the emojis (left) and taking into account the emojis (right) (Ayvaz and Shiha, 2017)

Ayvaz and Shiha (2017) pointed out that considering emojis in sentiment analysis improves the sentiment scores. Nevertheless, the occurrence of emojis with a positive sentiment score is higher than that of natural and negative ones. Consequently, exploiting emoji characters in sentiment analysis increases the general sentiment scores of positive opinions more than negative opinions (Novak *et al.*, 2015; Ayvaz and Shiha, 2017). Still, when tweets with emojis and without emojis were compared, it was found that the occurrence of emojis had a stronger impact on the emotional perception of tweets (Novak *et al.*, 2015).

The results show that the evaluation of sentiments using emojis has a unique ability, but it can be misleading and challenging if the weaknesses and limitations of using social media data are not taken into consideration.

Scholars in the Dresden University of Technology investigated reactions of people towards events based on LBSM posts and use of emojis (Hauthal, Burghardt and Dunkel, 2019). The case study was the withdrawal of the United Kingdom (UK) from European Union (EU), the Brexit event. They adopted two approaches: The first method was classifying emojis and hashtags as positive and negative classes, and consequently evaluating them together to determine a sentiment or a reaction. The second method was forming emotional categories like love, joy, surprise, anger, sadness, and fear and assigning emojis in these categories as an indicator of sentiments. The visualisation of the results is illustrated in Figure 10. According to the results, sentiment analysis combining hashtags with emojis reflected better results than only hashtag-based evaluations. They spotted the difficulty that use and conception of emojis differ among people and in "serious" topics like politics, users tend to use less emojis than other events.

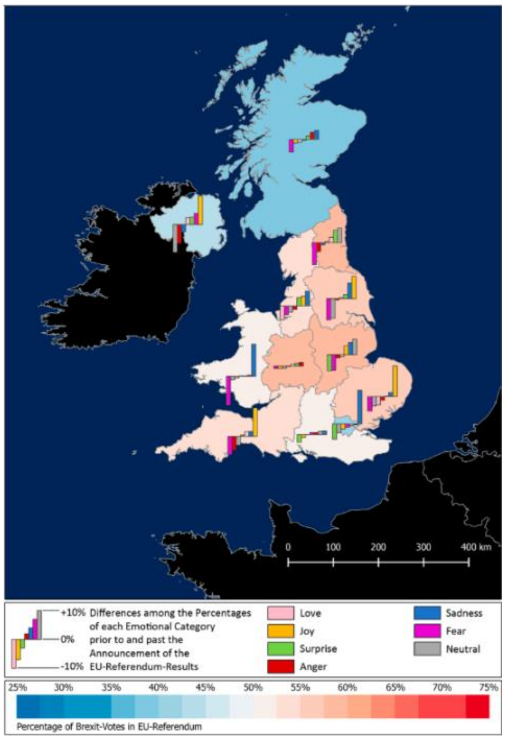


Figure 10. Change of percentages in emotions before and after the announcement of the referendum results visualised together with results of the EU referendum (Hauthal, Burghardt and Dunkel, 2019).

3. Methodology and Analysis of the Results

This section will discuss the methodology, the results, workflow and the overall approach to subjective value assessment based on emojis used in social media.

3.1. Workflow

The methodology was completed in three main steps in line with the research objectives, as illustrated in Figure 11. Main Workflow The methodology started with the data preparation and the data analysis, which aimed to prepare the basis for the next steps. Secondly, the categories of *activities, objects* and *sentiments* were completed considering most meaningful categories for urban studies. Emojis were then assigned to these three categories which were then used in geovisualisation process. All the posts in LBSM data in Dresden were categorised according to the emojis they contain. An interactive web map was developed to read, interpret and filter the LBSM data.

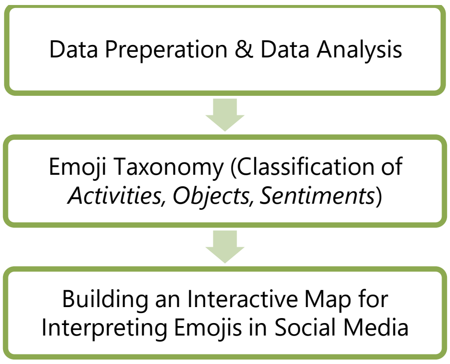


Figure 11. Main Workflow

3.2. Data Preparation and Data Analysis

3.2.1. The LBSM Data

The data used in this research consists of posts from Twitter, Instagram and Flickr that utilises a common LSBM data scheme (Dunkel, Löchner and Krumpe, 2019). Posts from Twitter, Flickr and Instagram were converted into the same format and a subset of this data was extracted as Comma Separated Values (CSV) (A. Dunkel, personal communication, August 28, 2019).

The data consists of posts with latitude, longitude, post creation date, post publishing date, post thumbnail URL, post view count, post like count, post URL, tags, emoji, post title, post body, post geo-accuracy, post comment count, post type, post filter, place name, place ID, user ID, post ID information. The data contains 1,073,095 posts, which were posted between the years 2007 – 2018. This data had a large size that would cause difficulties in processing and interpretation. Therefore, it was a prerequisite to reduce the data size to an amount that could be easy to handle. Reducing the dataset was handled in five steps:

(1) Posts which do not include any emoji were removed.

(2) Irrelevant information was deleted. The remaining columns were "post ID", "emoji", "latitude", "longitude", "post publish data", "tags", "post body", "place name".

(3) Individual emojis were assigned to separate rows. Their emoji code and emoji names were added (examples are shown in Figure 12 and Figure 13). After this step, the count of features increased from 192,254 to 369,477 because most posts included more than single emoji.

lat	lng	post ic	post_publi:	post_body	hashtags	emoji	loc_name
51.06828	13.75318	e5a8c4bc	06-08-18 9:48	Die Sonne scheint	life;neustadt;	☁, ☀, 📷	TEERAUSCH

Figure 12. A section from LBSM data in Dresden

lat	lng	post ic	post_publi:	post_body	hashtags	emoji_code	emoji_nam	emoji	loc_nar
51.06828	13.75318	e5a8c4bc	06-08-18 9:48	Die Sonne scheint	life;neustadt;	U+2601	cloud	☁	TEERAUSC
51.06828	13.75318	e5a8c4bc	06-08-18 9:48	Die Sonne scheint	life;neustadt;	U+2600	sun	☀	TEERAUSC
51.06828	13.75318	e5a8c4bc	06-08-18 9:48	Die Sonne scheint	life;neustadt;	U+1F4F7	camera	📷	TEERAUSC

Figure 13. A section from LBSM data in Dresden after separating emojis

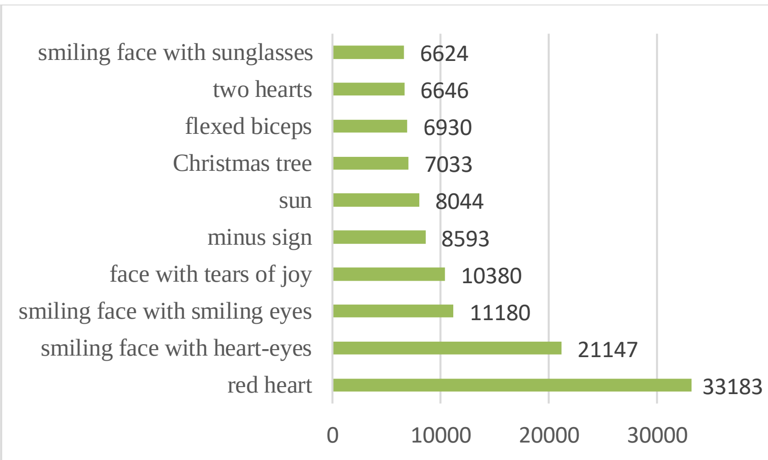
(4) Repetitious features, where the same emojis have been repeatedly used in the same post, were removed.

(5) Posts whose emojis were not assigned to any category were eliminated.

After these steps, 104,720 unique posts have remained within total 154,637 rows (points).

3.2.2. Emoji Usage in Posts

To develop an efficient approach in further steps, emoji usage in Dresden was analysed. As illustrated in Graph 1, the most used emojis were "red heart" (33183 times used), "smiling face with heart-eyes" (21147 times used), "smiling face with smiling eyes" (11180 times used), "face with tears of joy" (10380 times used), "minus sign" (8593 times used), "sun" (8044 times used), "christmas tree" (7033 times used), "flexed biceps" (6930 times used), "two hearts" (6646 times used), and "smiling face with sunglasses" (6624 times used).

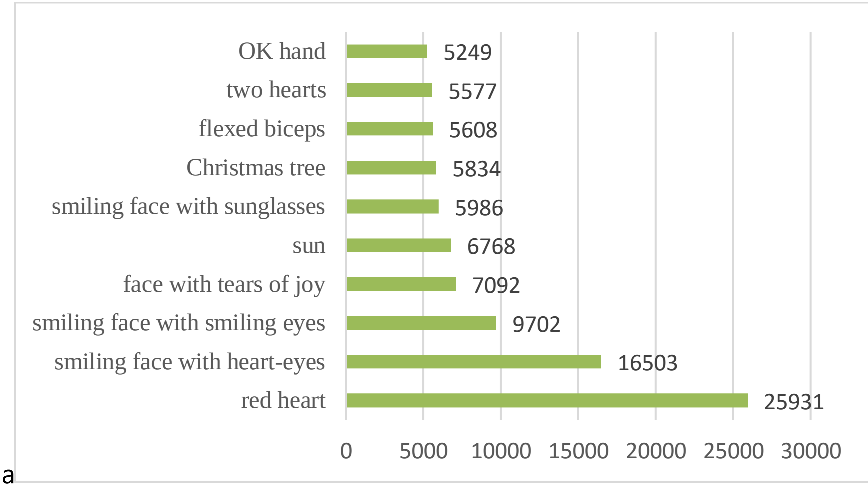


Graph 1. Most used emojis (including repeats)

PostID	EmojiCode	EmojiName
f2318f82158464f71c7a95f24731f549f9c2e3fd221f3e9567b334bde49a76f5	U+2764	red heart
f2318f82158464f71c7a95f24731f549f9c2e3fd221f3e9567b334bde49a76f5	U+2764	red heart
f2318f82158464f71c7a95f24731f549f9c2e3fd221f3e9567b334bde49a76f5	U+2764	red heart

Figure 14. Example of repetition

These emojis were used multiple times in posts, as seen in Figure 14. Another analysis was performed to find the number of emojis without repetitions. After excluding duplicates, a change in the number of emojis could be observed. Graph 2 displays the first 10 most used emojis out of 1053 unique emojis that were found in the data.



a

Graph 2. Most used emojis (excluding repeats)

3.3. Emoji Taxonomy

This chapter will discuss the approach to assign emojis into categories. The result of emoji taxonomy can be seen in the table in Appendix A.

3.3.1. Classification of Activities, Objects, Sentiments

There are eight categories in standard emoji categorisation; Smileys & People, Animals & Nature, Food & Drink, Activity, Travel & Places, Objects, Symbols, Flags ('Emoji Version 11', 2018). It is evident that emojis can present not only emotions but also a wide range of activities, such as swimming, biking, shopping, eating or spatial areas and landmarks like school, church, mountain.

In this research, categorisations were used to provide the most meaningful interpretation of emojis for urban studies. For the emoji taxonomy, firstly main categories, then subcategories were determined. Main categories were determined as *objects, activities* and *sentiments*. They were then subdivided, and emojis were assigned to these subcategories. In doing so, two points were considered: (1) Degrees of relation to activities (for the category *activities*), spatial areas and landmarks (for the category *objects*) and emotions (for the category *sentiments*) in a city, (2) the likelihood that these categories can be represented by an emoji.

3.3.1.1. The Categorisation of Activities

The main category *activities* were divided into subcategories by focusing on basic activities happening in cities. In a study, which analysed human activity and mobility patterns using LBSM data, activities were subdivided into 6 categories as "Home", "Work", "Eating", "Entertainment", "Recreation", "Shopping" according to type of visited locations and check-ins (Hasan, Zhan and Ukkusuri, 2013). However, this research aimed to provide a more detailed perspective on recreational activities. Thus, a subdivision of recreational activities was necessary.

Metin and colleagues (2017) created an inventory list of recreational activity types to be used in scientific researches. In their research, landscape architects, academicians in sport science and tourism contributed to this list of activities. The inventory list helped to outline the "Recreational" subcategory section in this study. In the end, a subdivision of *activities* for this research formed under six subcategories: "Eat & Drink", "Shopping", "Work", "Basic Entertainment", "Mental Activity & Relaxation", "Outdoor Activities & Sports". As aforementioned, the competence of representation by an emoji and its relation to urban places/studies were the primary considerations. Figure 15 illustrates the subclassification with related keywords to be used in emoji taxonomy.

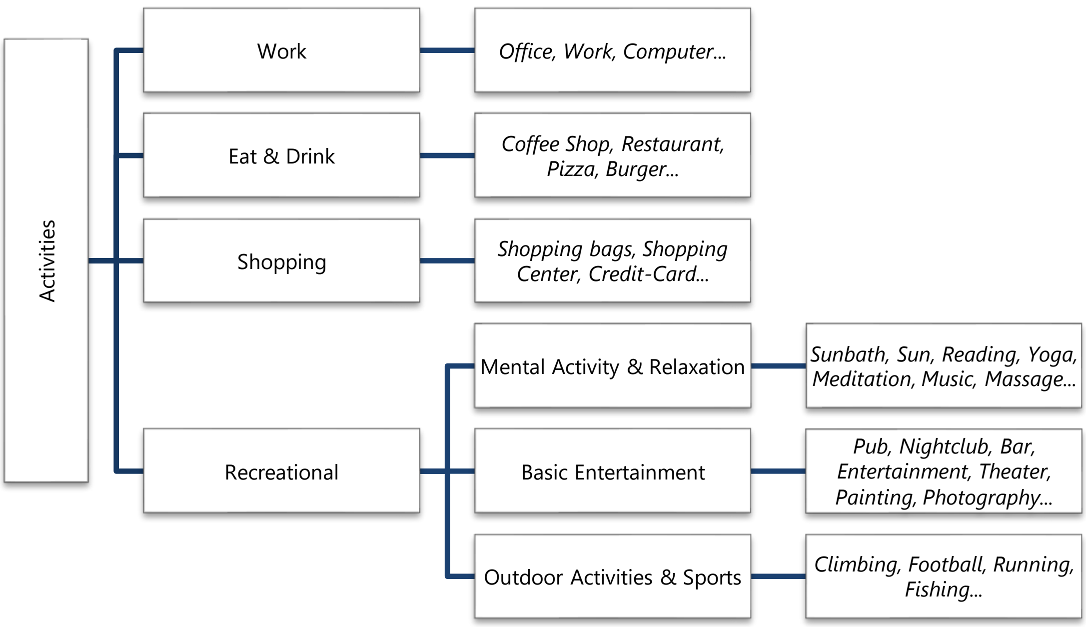


Figure 15. Categorisation of *activities*

3.3.1.2. The Categorisation of Objects

In this context, *objects* refer to the perceived objects represented in the city. Particular emphasis placed on the perception of spatial areas and public perception as an assessment for the quality of land use (Qu *et al.*, 2018). Scholars argued that integrating public perception into planning allows planners to manage urban issues in an "inclusive" and "equitable" way and provides control for future actions (Liepa-Zemeša and Hess, 2016).

This study explored the extent to which emojis can represent public perception through urban land use and landmarks. The primary purpose of using *objects* as spatial features was to evaluate how possible it is to identify land uses and landmarks based on the use of emojis.

The subdivision of *objects* was made considering the main land uses and the capability of the representation by emojis. The wide range of emoji includes emoji showing various buildings like school, church, house; modes of transport like bus, train, taxi and locations like the stadium, beach ('Emoji Version 11', 2018).

Anderson (1976) listed the land uses in 2 levels: 1st level corresponds to main categories like "Urban or Built-Up Land", "Agricultural Land", "Forest Land" and 2nd level includes subcategories of the main categories. The subdivision of *objects* benefited from the category "Urban or Built-Up Land" from Anderson's study and other land uses were left out since they were unrelated to this investigation.

Built-up lands are where most of the surface is covered by structures and cities, towns, highways, transportations and communication facilities, shopping and commercial centres belong to this category (Anderson, 1976). Referring to Anderson's (1976) research, the *objects* main category were subdivided into four classes with few alterations. For example, Anderson (1976) did not include recreational land use in 1st level categories claiming that recreation-oriented land use can be found in many other land uses, such as commercial and services. In this classification, "Recreational Open Space" subcategory represents recreational areas, parks and green spaces. The subcategories of *objects* are shown in Figure 16.

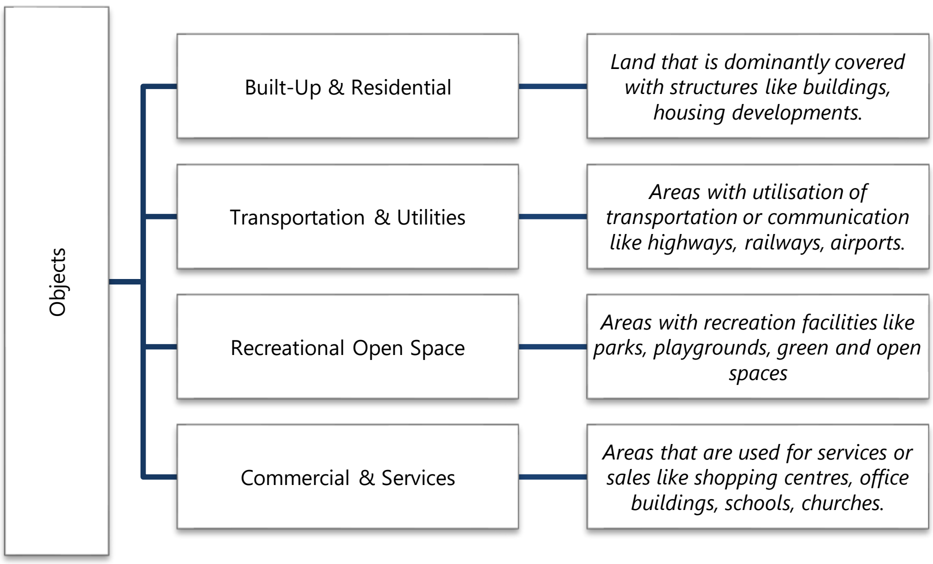


Figure 16. The categorisation of *objects*

3.3.1.3. The Categorisation of Sentiments

Emotions are the origin of different experiences and behaviours, and the environment plays a vital role in the emotions of individuals (Ulrich, 1983). Taking into consideration that urban planning ensures communities' welfare, as well as the development of areas, the analysis of opinions and sentiments of citizens is valuable for successful planning implementations. Due to the complexity of urban nature and limitations of methods, scaling subjective values is challenging. However, a large amount of social media data gives a possibility to assess the sentiments of people by analysing their geolocated posts.

The aim of having a *sentiments* main category for the emoji taxonomy was visualising the emotions of people in urban areas according to the use of emoji. By doing this, it would be possible to observe the emotions and the degree of satisfaction in an urban area. A straightforward method was adopted to subdivide the main category *sentiments*. According to their polarity, *sentiments* were subdivided as positive, negative, neutral, and emojis were assigned to these groups.

Positive psychology defines positive emotions as valued subjective experiences of well-being, hope and optimism (Csikszentmihalyi, 2000). The subcategory "Positive" here conceptualises well-being, positive experiences and states like love, happiness, joy, hope, compassion, gratitude. Negative emotions were described as "unpleasant or unhappy emotion which is evoked in individuals to express a negative affect towards an event or person" (Pam M.S., 2013). Universal negative emotions are anger, disgust, sadness, fear, loneliness, melancholy, annoyance (Ackerman, 2019). Lastly, neutral emotions are a type of feelings that are neither unpleasant nor pleasant (Anālayo, 2017). Emotions like surprise, indifferent, dull, cold, bored, weary were included in the "Neutral" subcategory.

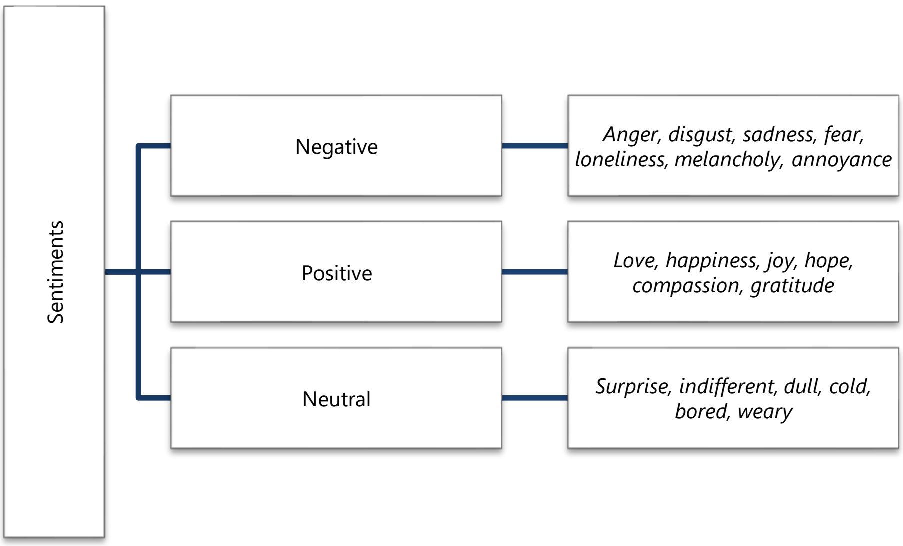


Figure 17. The categorisation of *sentiments*

3.3.2. Assigning Emojis into Activities, Objects, Sentiments

In this section, a suitable approach for assigning emojis into defined categories will be discussed. The assignment was performed separately for each main category; *activities, objects, sentiments*. The approach for assigning emojis for *activities* and *objects* was matching keywords that were previously defined when subdividing the main categories (discussed in Section 3.3.1.1 and 3.3.1.2) with emoji names from Unicode emoji character list. Emojis were assigned to *sentiments* according to their sentiment scores from the study of Novak, Smailović, Sluban, and Mozetič (2015), which was previously discussed in Section 2.3.

3.3.2.1. Activities

(1) Defining keywords

In "Eat & Drink" subcategory, all emojis in "Food and Drink" category from the Unicode list were assigned ('Emoji Version 11', 2018). However, for categories like "Basic Entertainment", "Outdoor Activities & Sports" there were no formerly grouped emojis. Therefore, suitable keywords for each category from literature research (as discussed in Section 3.3.1.1) were formed. Emojis which were overly encountered in posts were approached carefully; e.g. *tree* or *sun* as keywords can indicate activities outside, and the emojis representing these words could be counted in "Outdoor Activities & Sports". However, emojis "christmas tree" and "sun" were some of the most used emojis in LBSM data in Dresden. Therefore, these emojis were removed to prevent misleading results.

(2) Matching keywords

In order to match keywords with emoji names, in Excel, SEARCH function together with INDEX and MATCH was used (Table 1 and Table 2).

```
=INDEX(Keywords[[#All],[Categories]],MATCH(TRUE,ISNUMBER(SEARCH(Keywords[[#All],[Keywords]],[@EmojiName])),0))
```

EmojiName	Category
artist palette	basic entertainment
camera	basic entertainment
camera with flash	basic entertainment
cinema	basic entertainment
film frames	basic entertainment
film projector	basic entertainment

Table 1. Matching keywords with emoji names

Keywords	Categories
artist	basic entertainment
camera	basic entertainment
cinema	basic entertainment
film	basic entertainment

Table 2. Keywords for categories

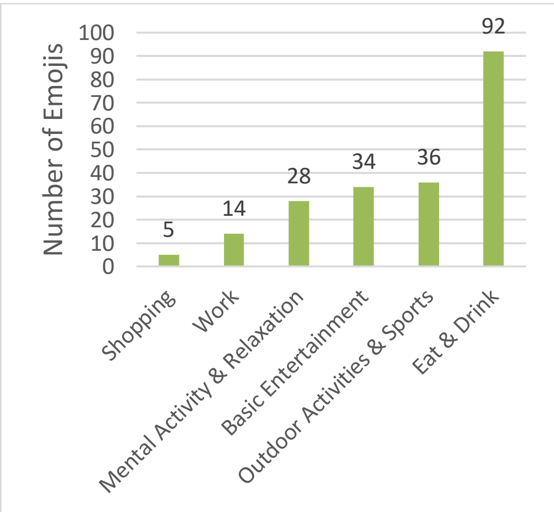
(3) Filtering

One drawback of this approach was that irrelevant emojis were also assigned to categories due to the matching keywords. Therefore, the process of selecting and removing unrelated emojis and adding the proper emojis was applied. For example; the keyword *park* belongs to the category "Outdoor Activities". However, all emojis containing the name *park* were assigned to "Outdoor Activities" like "sparkles" (✨), "sparkler" (🎇), "sparkling heart" (💖). Thus, the word *park* was removed, and the emoji "national park" (🏞) was inserted into the category.

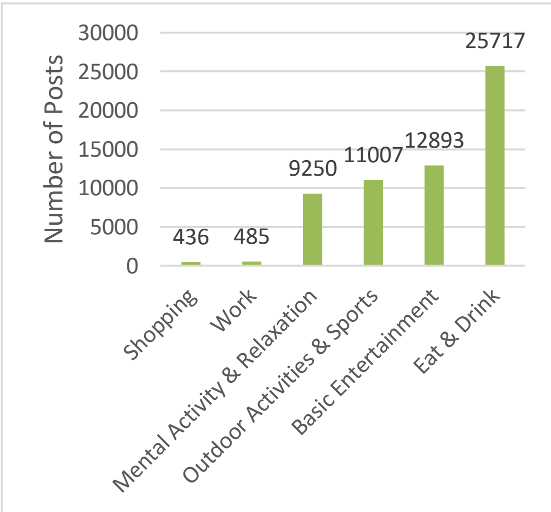
(4) Assignment of posts to categories based on the emojis they contain

After the first three steps employed, 238 emojis out of 1053 were assigned to *activities* category. Graph 3 indicates the distribution of emojis that were placed in one of the *activity* subcategories. Most emojis were assigned to "Eat & Drink", and only five emojis were assigned to the "Shopping" subcategory.

Posts with multiple emojis were counted multiple times and treated as separate posts. One post could be categorised into multiple categories. 65,835 out of 369,480 points were categorised, including the same posts with different emojis. The distribution of the number of posts assigned to the *activities* category can be seen in Graph 4. The most found emojis in the *activities* category is shown in Table 3.



Graph 3. Number of assigned emojis in *activities* category



Graph 4. Count of posts in *activities* category

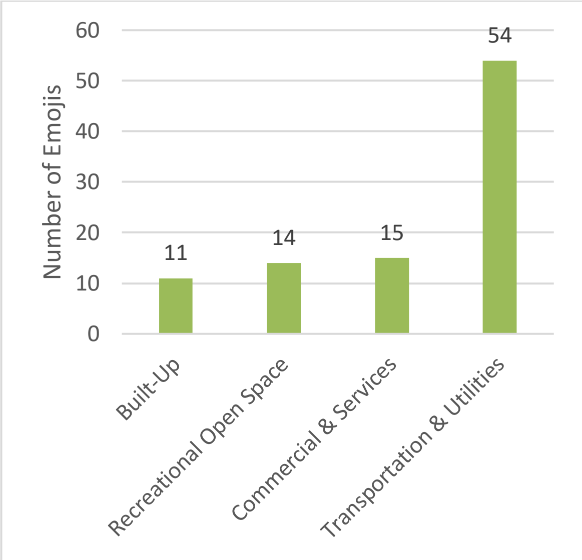
Emoji Name	Emojis	Number of Posts (Points)
eat & drink		
face savouring food	😋	3453
hot beverage	☕	2082
wine glass	🍷	1861
outdoor activities & sports		
flexed biceps	💪	5608
person running	🏃	1220
soccer ball	⚽	992
basic entertainment		
camera	📷	3542
camera with flash	📸	3107
woman dancing	💃	1593
mental activity, relaxation		
musical notes	🎶	1540
beer mug	🍺	984
sunrise	🌅	785
shopping		
shopping bags	🛍	315
shopping cart	🛒	86
credit card	💳	19
work		
laptop computer	💻	238
desktop computer	🖥	86
necktie	👔	71

Table 3. Mostly used emojis for each activity subcategory

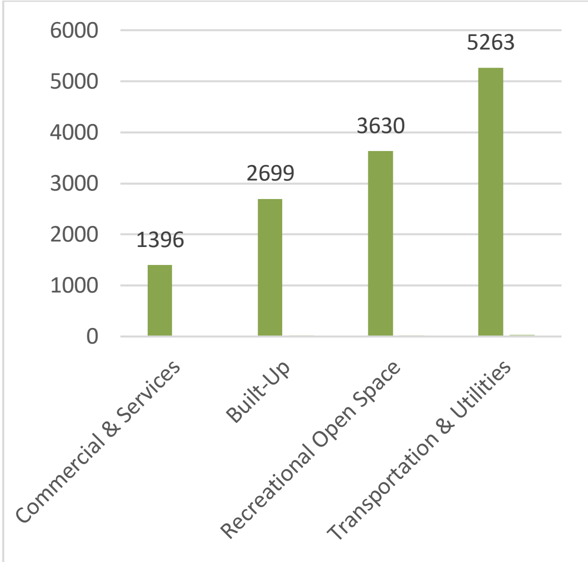
3.3.2.2. Objects

A similar approach was used for assigning emojis in the *objects* category. Main keywords were defined for every 4 subcategories, and the terms were matched to Unicode emoji names. Afterwards, emojis in Travel & Places from default category which contains emojis for locations, buildings and modes of transport ('Emoji Version 11', 2018) were also added, in addition to emojis which were automatically assigned after keyword matching process. For example, "baggage claim" (🛄) and "left luggage" (🛅) were added to "Transportation & Utilities" considering they indirectly indicate airports.

In the end, 94 emojis out of 1053 emojis were assigned to one of the subclasses of *objects* category. Graph 5 demonstrates the partitioning of emojis in the categories; 54 emojis in "Transportation & Utilities", 15 emojis in "Commercial & Services", 14 emojis in "Recreational & Open Space" and lastly 11 emojis in "Built-Up & Residential" subcategory were assigned. Subsequently; 12,988 out of 369,480 points were assigned to a subcategory of *objects*. Even though only 14 emojis were representative for "Recreational & Open Space" category, a significant portion of points (28%) were assigned to this category. The most used emojis in *objects* category are indicated in Table 4.



Graph 5. Number of assigned emojis in *objects* category



Graph 6. Count of posts in *objects* category

Emoji Name	Emojis	Number of Points
built-up & residential		
castle	🏰	1308
church	⛪	521
classical building	🏛	480
commercial & services		
locomotive	🚂	284
oncoming automobile	🚘	247
bus	🚌	175
recreational & open space		
sunrise	🌅	785
sunset	🌇	460
national park	🏞	427
transportation & utilities		
airplane	✈	921
automobile	🚗	491
bicycle	🚲	458

Table 4. Mostly used emojis in *objects* category

3.3.2.3. Sentiments

The approach to assign emojis to *sentiments* subcategories (“Negative”, “Natural”, “Positive”) was different from previous approaches. For assigning emojis in *sentiments* category, the sentiment ranking of emojis from Novak's study was utilised (Novak *et al.*, 2015).

(1) Selection of emojis

Emojis were selected from Smileys & People default category of Unicode list (‘Emoji Version 11’, 2018). The criterion was to find emojis with facial expression and a clear gesture. In total, 86 emojis were selected to be assigned to one of the subcategories of *sentiments*.

(2) Ranking emojis with the help of "Emoji Sentiment Ranking v1.0" (Novak *et al.*, 2015)

Sentiment rankings for each emoji were found from the list "Emoji Sentiment Ranking v1.0". Emojis which the list did not include, were scored the same with the most similar emoji; e.g. "face with rolling eyes" (🙄) was not ranked. Therefore, the same score for emoji "unamused face" (😒) was inserted for "face with rolling eyes".

Emoji Name	Emoji	Sentiment Ranking
neutral face	😐	-0.388
weary face	😩	-0.368
anguished face	😧	-0.063
flushed face	😳	0.018
smiling face	☺️	0.657
kissing face with closed eyes	😚	0.71

Table 5. A sample part of Sentiment Ranking (Novak *et al.*, 2015)

(3) Dividing emoji list equally into three sections according to their ranking and assigning in subcategories

The list of emoji sentiment ranking was ordered from smallest to largest, and deciles were calculated to divide the list into equal parts. The values were then divided into three parts from 4th and 7th decile. Later, emojis were assigned to "Negative", "Neutral" and "Positive" subcategories of *sentiments* (shown in Table 6).

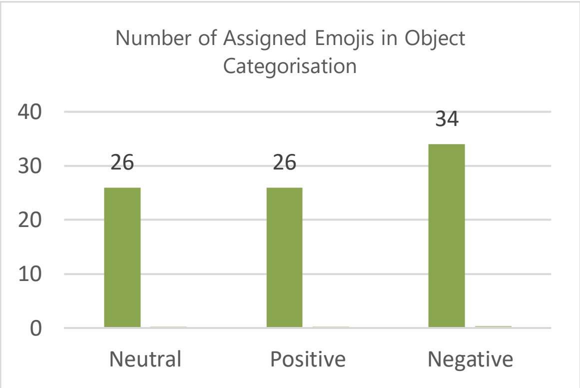
	Negative			Neutral			Positive		
Decile	1st decile	2nd decile	3rd decile	4th decile	5th decile	6th decile	7th decile	8th decile	9th decile
Value	-0.368	-0.311	-0.15	-0.08	0.085	0.221	0.410	0.486	0.625
Interval	-0.08 > x			-0.08 ≤ x < 0.410			0.410 ≤ x		
Nr. of Assigned Emojis	34			26			26		

Table 6. Deciles of emoji sentiment scores

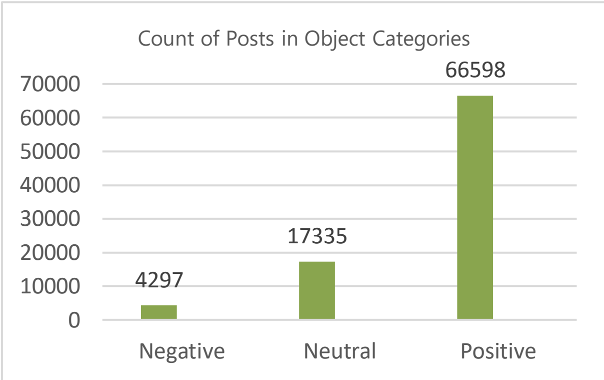
Emoji Name	Sentiment Ranking	Emoji	Number of Points
negative			
face with rolling eyes	-0.374	🙄	838
loudly crying face	-0.093	😭	654
pensive face	-0.146	😔	392
neutral			
face with tears of joy	0.221	😂	7092
grinning face with sweat	0.178	😅	3086
smirking face	0.332	😏	1356
positive			
smiling face with heart-eyes	0.619	😍	16503
smiling face with smiling eyes	0.644	😊	9702
smiling face with sunglasses	0.491	😎	5986

Table 7. An example of categorisation of emojis for each sentiment subcategory

In total, 86 emojis were assigned to *sentiment* category (shown in Graph 7). Even though most emojis were assigned to "Negative" comparing to "Neutral" and "Positive" (illustrated in Graph 7), only 5% of posts were assigned as "Negative", and big portion (75%) of posts were assigned as "Positive" (shown in Graph 8).



Graph 7. Number of assigned emojis in *sentiments* category



Graph 8. Count of posts in *sentiments* category

After completing the assignments, the emoji taxonomy was generated (as shown in Appendix A). Besides, a new data table was created consisting of posts, including post ID, emoji code, emoji name, latitude, longitude, post publish date, tags, post body, place name, category activity, category object, category sentiment information was created to be used in geovisualisation process.

3.4. Geovisualisation of Emojis in LBSM Posts in Dresden

In this study, it was deduced that the most appropriate approach to present the LBSM data was adopting a digital interactive geovisualisation method, as discussed in Section 2.1.1. Geographic visualisation plays an essential role in this research since created categorisations, and processed data are complex to read without informative representations. As a solution to this complexity, an interactive web map was set up to visualise Dresden LBSM posts based on the emoji taxonomy and the categories they were assigned to. The main aim of developing a web map application was giving users the opportunity to observe relationships between *activities, objects* and *sentiments*. Created web map can be found under this link:"https://elifcanozyildirim.shinyapps.io/mapemoji/".

3.4.1. Chosen Environment and Libraries

The map was created utilising the *Leaflet* library in R environment. *Leaflet* is an open-source JavaScript library and comprises of features like map controls, zoom buttons, layer switcher; visual features like markers and pop-ups and interaction features like drag panning and double click zoom. *Leaflet* can add geoJSON, WMS layers; markers and popups to the web map. The R package *Leaflet* enables *Leaflet* maps and other applications such as *Shiny* to integrate into the R.

R is a language and environment for statistical computing, which also enables data analysis and graphical display. Since it is open source and has been widely accepted by statisticians and data scientists (Beeley, 2013), R language and *Shiny* package were found to be most suitable for use when creating the web map. *Shiny* is an R package used for building interactive web apps through R environment (Team, 2016). The R package *Shiny* was utilised because it uses a reactive programming model and facilitates presenting interactive data summaries and queries to end-users with a web browser (Beeley, 2013). The map for this research was created in RStudio *Leaflet* library was used and integrated into a *Shiny* web application. Simple creation of *Leaflet* map in RStudio is as shown below.

```
library(leaflet)
m <- leaflet({
  leaflet() %>%
    setView(13.74518, 51.04828, zoom = 13)  %>%
    addProviderTiles(providers$CartoDB.Positron, group = "Positron (de-
fault)")
```

Shiny applications contain two sections one as server function defining server components and one User Interface (UI) section defining layout and the appearance of the app. UI section compromises of web elements where users modify input; interact and manipulate the data by widgets. When the user changes the input widget, the output is promptly rendered in the server section. *Leaflet* packages can be integrated into *Shiny* applications by registering the output as `leafletOutput()` in the UI section and assigning `renderLeaflet()` expression in server to render the *Leaflet* map, as shown in the following code.

```
library(Shiny)
library(leaflet)

ui <- fluidPage(
  leafletOutput("MyMap"),
)
server <- function(input, output, session) {
  output$MyMap <- renderLeaflet({
    leaflet() %>%
      setView(13.74518, 51.04828, zoom = 13)  %>%
    addProviderTiles(providers$CartoDB.Positron, group = "Positron (de-
fault)")   })
}
ShinyApp(ui, server)
```

3.4.2. Design and Development of the Interactive Geovisualisation

3.4.2.1. Main Page

Server-side and UI side of the application for the interactive web map were handled in separate two files as *server.R* and *ui.R*, since having separate files make the code easier to handle. The global environment was defined in *global.R*. The navigation bar on the web app contains three tabs: “Map”, “Heat Map” and

"Emoji Categorization and Wordcloud". Firstly, UI was built using `tabsetPanel()` function and in the server, the partials (*Map.R, Wordcloud.R* and *Table.R*) files were sourced. The UI side of each tab was saved in the file name "UIfiles", and the server part was saved in "serverfiles" (shown in Figure 18).

```
  tabsetPanel(id = "partial", type = "pill",
    tabPanel("Map", value="map"),
    tabPanel("Emoji Categorization and Wordcloud ", value="wordcloud"),
    tabPanel("Heatmap", value="heatmap")
  )

function(input, output, session) {
  output$output <- renderUI({
    source(file.path("UIfiles", paste0(input$UIfiles, ".R")), lo-
cal=TRUE)$value
  })
  for (file in list.files("serverfiles")) {
    source(file.path("serverfiles", file), local = TRUE)
  }
```

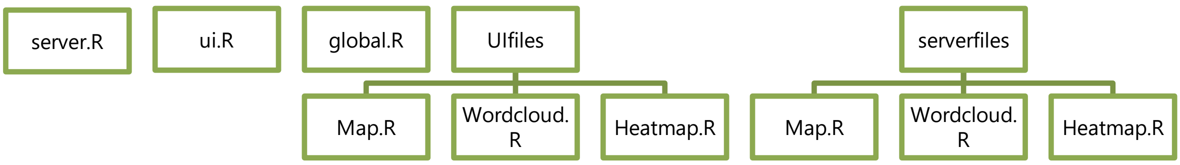


Figure 18. File order

The tab "Map" is the start page, where the user can filter and visualise the main and subcategories on the map as cluster points. The table showing social media posts including the information of body of the posts, hashtags, emojis and locations was added under the map. "Heatmap" visualises the points similar to the first map in "Map" tab but without cluster points and using warm and cold colours to show the density. "Emoji Categorisation and Wordcloud" was generated to inform users about trends in emoji usage and which emojis were assigned to which category.

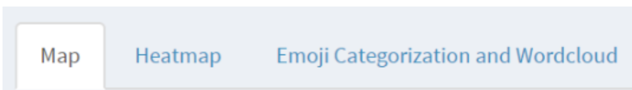


Figure 19. The navigation bar in the web app

3.4.2.2. The Main Page

The start page that allows analysing categories consists of three components: (1) Control panel for filtering categories and changing data range, (2) the interactive map, (3) the table with all posts including searching and filtering options for each column.

The table with generated categories was uploaded to RStudio. Filter options were provided by using `awesomeCheckboxGroup()` and `dateRangeInput()` in the UI.

```
awesomeCheckboxGroup(
        inputId = "sentiment",
        label = "Sentiments",
        choices = var_sentiment,
        inline = F,
      ),
      dateRangeInput(
        'dates',
        label = "Date Range",
        start = "2018-01-01",
        end = "2019-01-01",
        min = "2008-01-01",
        max = "2020-01-01"
      )
```

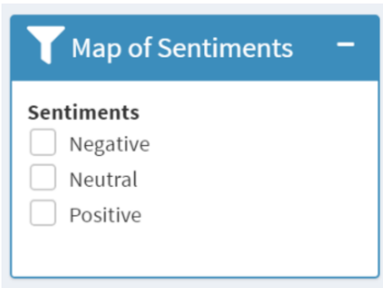


Figure 20. The checkboxes for *sentiments* category

Reactive expression was used for filtering the data for each category. Reactive expressions can read the reactive value, also can call other reactive expressions. Depended reactive expressions are re-executed when reactive value changes (Team, 2016). The following is a code sample to filter the main category of *sentiments* and the date of the posts. Anytime the input via checkboxes are changed, the data is filtered accordingly, and markers appear on the map according to the user's input.

```
filtereddata_object <- reactive({
  data %>%
    filter(category_object %in% input$object)  %>%
    filter(post_date > input$dates[1] &
             post_date < input$dates[2])
})
addAwesomeMarkers(
      data = filtereddata_object(),
      lng = ~ longitude,
      lat = ~ latitude,
      popup =  popup =  paste(
        "ID Number:",
        filtereddata_object()$ID ,
        "<br>",
        "Categories: ",
        filtereddata_object()$content,
        "<br>" ,
```

```
        "Emojis:",
        filtereddata_object()$emoji,
        "<br>",
        "Place Name: ",
        filtereddata_object()$place_name
      ),
      clusterOptions = markerClusterOptions(
        showCoverageOnHover = FALSE,
      )
  )
```

This process was repeated for each category. The markers were used with clusters using `markerClusterOptions()` because points were concentrated in certain areas and using cluster points could improve the readability of the map. In addition, cluster points allow the map to be rendered relatively quickly.

Green spaces were emphasised by adding a new layer of geoJSON file (green.geojson) which includes polygons of green spaces in Dresden. An action button was added in the UI side, and `observeEvent()` function was used to add polygons when the button is clicked.

```
actionButton("greenspace", "Highlight Green Spaces", color = "black", style
= "material-flat")
           )
greenspaces <- geojsonio::geojson_read("green.geojson", what = "sp")
 observeEvent(input$greenspace,  {
  leafletProxy("MyMap") %>%
    addPolygons(
      data = greenspaces,
      stroke = FALSE,
      smoothFactor = 0.9,
      fillOpacity = 0.4,
      fillColor = "green",
      group = "objects"
    )
```

The interactive map represents posts that were categorised to show activities, spatial patterns and feelings. Filtering tools were integrated to filter categories and enable interpretation and modification of the data. Visualising data by categories makes the interpretation of social media data more readable. This facilitates to observe activities concentrated in places, spatial patterns and sentiments of people.

In *objects* categorisation, emojis were chosen to represent the physical characteristics of the terrain from the users' perspective and experience. Cluster points that can be filtered in the *objects* category indicate location patterns and spatial distribution within the city. Filtering of the *activities* category allows the user to read the community's habits, activities and social behaviour, and to analyse which activities are performed more frequently. Lastly, filtering of *sentiments* category, which was divided into "Negative", "Neutral", "Positive" is most effectively used when investigated together with other categories to see the relationship between activities, spatial patterns and emotions.

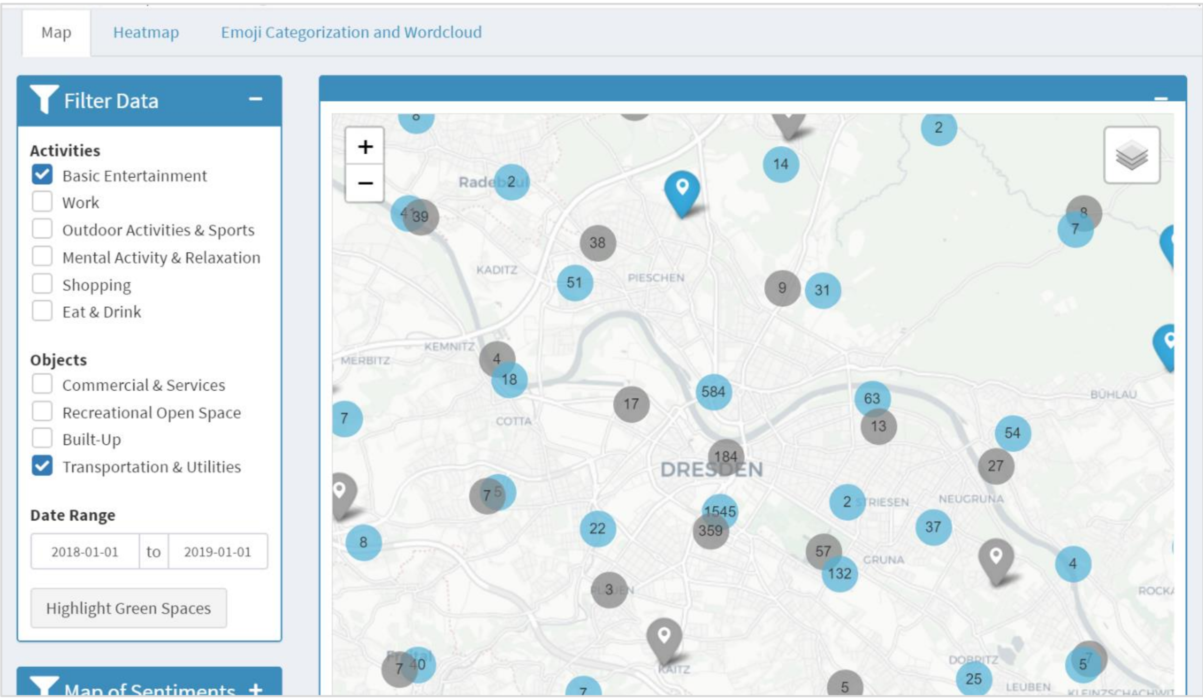


Figure 21. The interface of the map

Another filtering option where a detailed list of "Outdoor Activities & Sports" was given as checkboxes under the title "Outdoor Activities & Sports". This list of filtering options was created to let the user discover specific activity types. The list of checkboxes includes following activities: "Weight Lifting (Fitness), "Fitness", "Bicycle Riding", "Football", "Running", "Swimming", "American Football", "Rowing", "Sailing", "Volleyball", "Fishing", "Bowling", "Tennis", "Basketball", "Hockey", "Golf", "Badminton", "Baseball", "Canoe", "Rugby".

A table with a piece of detailed information about all posts was inserted on the start page below the map. The main aim behind including the data table was allowing users to investigate the posts in more detail. Posts with categorisations were organised and integrated into the web map. Besides emojis, the body of the post, hashtags and place names were added to the table.

```
output$table <- DT::renderDataTable(
  DT::datatable(data_table, options = list(pageLength = 25, scrollX = TRUE,
autowidth= T)
  ))
```

In addition to discovering keywords in posts, a critical feature that this table provides is exploring the used emojis together. After generating the emoji taxonomy, emojis found in posts were separated and treated as individual posts, as examples were given in Figure 12 and Figure 13. However, it is crucial to see which emojis were used exactly with which emojis, to capture the social media user's perspective in a more comprehensive manner. The table shows not only the body of the post but also all emojis on the post body. The table was linked to the map so that the positions of the posts could be indicated by a marker when clicked.

3.4.2.3. The Heatmap

A heat map is a visualisation tool that uses warm and cool colours spectrum like red, yellow, green and blue to indicate where points are relatively concentrated. This map was created as an addition to the first map with cluster points. The heatmap allows users to see the patterns better than cluster points, which facilitates comparison, particularly when comparing temporal changes.

By reading the heatmap, users can identify patterns (an example is shown in Figure 22). Just like the first map with cluster points, all data filtering options were inserted on the panel. In this case, having multiple category layers at the same time is not explanatory for the map user, but it gives a better insight both contextually and informatically when only one of the *activities, objects* or *sentiments* category is applied.

```
addTiles(group = "OSM", options = providerTileOptions(opacity = 0.85)) %>%
    addHeatmap(data= filtereddata_activity(), lng=~ longitude,lat=~ latitude,
blur = 20, max = 0.05, radius = 15)
```

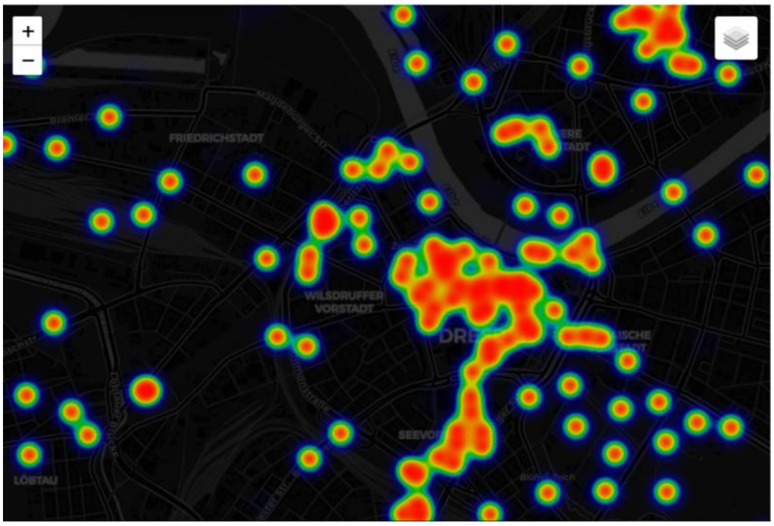


Figure 22. The heatmap showing “Transportation & Utilities” from *objects* category

3.4.2.4. Wordcloud

A word cloud is a two-dimensional graphical representation created by plotting the most common words in a text. In a word cloud, the font size of the word is determined by the frequency of words. Word clouds are easy to interpret the text, and they are aesthetically pleasing (Castellà and Sutton, 2014). As an innovative approach to give more insight about emoji usage in Dresden social media posts, a word cloud was generated with pictorial symbols of emojis and emoji names. Castella and Sutton (2014) agreed that seeing a picture is more comfortable than reading a text. Unlike regular word clouds, emojis were graphically plotted (Figure 24).

After data processing and analysis, a new data table was generated. The new table included the information about the emoji names, emoji code, emoji symbol, the categories to which they were assigned, and the total number of uses of these emojis in LSBM data. Table 8 is an example representing a small section of the data table. Appendix B demonstrates word clouds of emojis for the three categories.

Emoji Code	Emoji Name	Emoji Symbol	Count	Category Activity	Category Sentiment	Category Object
U+1F60E	smiling face with sunglasses	😎	5986		Sentiments	
U+1F60D	smiling face with heart-eyes	😍	16503		Sentiments	
U+1F4F7	camera	📷	3542	Activities		
U+1F618	face blowing a kiss	😘	4103		Sentiments	
U+263A	smiling face	☺	3535		Sentiments	

Table 8. An example of the data table

This data was used to create a word cloud to give the user more information about emoji taxonomy. Additionally, informing the user about the characteristics of social media data in Dresden was also possible by generating a word cloud. The following options were provided to the user: Choice of the category between *activities, objects, sentiments*; creating a word cloud that graphically draws emojis or creating a word cloud that draws emoji names as can be seen in Figure 24 , choice of the minimum number of emoji usage in data, choice of the maximum number of emojis in the plot (shown in Figure 23).

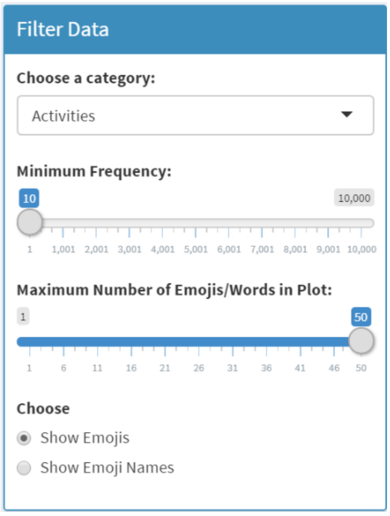


Figure 23. Given options to the user to plot the word cloud

The function `wordcloud()` was used to generate the plot.

```
wordcloud(words = filtered()$EmojiName, freq= filtered()$Count,scale=c(7,1),
random.order = FALSE, min.freq = input$freq, max.words=input$max,
                        colors=brewer.pal(8, "Dark2")) }
```

Figure 24 illustrates two plots of categories emojis in the *activities* category. The font size of emoji names and icon size of emojis are scaled depending on their occurrence. Some of the most frequently used emojis can be easily distinguished as "camera", "face savouring food", "hot beverage".

Figure 24. Word cloud of most used emojis as graphics and as text

4. Use Case Scenarios

This chapter will firstly present brief information about the City of Dresden. Secondly, it will discuss two examples to test the feasibility of assessment of urban and landscape planning using the interactive map based on social media posts in Dresden.

Dresden is a city in Germany and the capital of the state Saxony with a population of about 550,000. The city had faced extreme urban destruction during World War II, and because of this dramatic loss, the infrastructure of the city, housing and industry had to be rebuilt. Especially after the reunification of Germany in 1990, urban renewal had gained importance and citizens had been in solidarity for development of the city. Today, urban renewal in Dresden is of great importance, aiming to develop and maintain existing structures, neighbourhood and overall environment (Landeshauptstadt Dresden, 2015). The districts in Dresden are quite different, so the development process has been complicated. Development needs to be shaped by paying attention to urban and socio-structural features. (Landeshauptstadt Dresden, 2015).

4.1. Landscape Development and Open Space Planning

The presence of the fundamental relationship between physical activities and environment cannot be ignored (Joassart-Marcelli, 2010). The interaction between environmental conditions and leisure experiences works in two ways. Recreational activity patterns are shaped by the environment, and environmental conditions are affected by recreational activities (Jansen-Verbeke, 1988). Consequently, an essential dimension of leisure activities is the planning of the environment, and an essential aspect of environmental planning is the leisure activity patterns. Leisure activity patterns tend to change by time and making more effective planning decisions requires extensive research on behaviours in the city.

The social media and emoji usage examined in Dresden provide information about the leisure activities in the parks. This information gives an opportunity to observe the way residents use the parks. Using social media is not limited to any age, gender or nationality. Therefore, the scope of this information is broad and includes clues about a large group of people. For example, the geovisualisation shows which park in Dresden is most preferred and what kind of activities are carried out.

Resources and funding are important for landscape planning, and they are usually unevenly distributed in the parks (Joassart-Marcelli, 2010). In order to determine this, it is necessary to characterise the parks, e.g., analysing regular activity types and visitor density in parks. In a publication called "In Dialogue about Urban Transformation", the following question was asked: " What should be the amount, connection and quality of green and open spaces to be safeguarded or redeveloped?" (City of Munich and EUROCITIES, 2014).

The posts in LBSM data that were assigned to a category based on emoji taxonomy can assist in characterising the parks. For example, the *activities* category can assist in ranking the maps according to the numbers of cluster points shown in the web map. More cluster points indicate higher visitor intensity. Combining it with *sentiments* category can indicate the activities performed, plus the emotions that develop accordingly. Analysing hotspots and most visited parks facilitate to identify points of interest and preferred places. The concentration of recreational activities in only one region may indicate the need to plan other recreational areas, having in mind that all citizens living in the city should have equal access to recreational open spaces.

The questions below were answered by discovering the web map and exploring the LBSM data for the following parks in Dresden: Großer Garten, Sportpark Ostra, Waldpark Blasewitz, Blüher Park, Alaunpark and the open space in Elbwiesen (Figure 25).

- What are the typical activities in parks?
- Which parks are trendier in the city? Is there a significant change in the type of activities or frequency of visits by time?
- Are parks and recreational activities concentrated in one area or distributed evenly? Are there areas which could potentially be used and developed in the future?

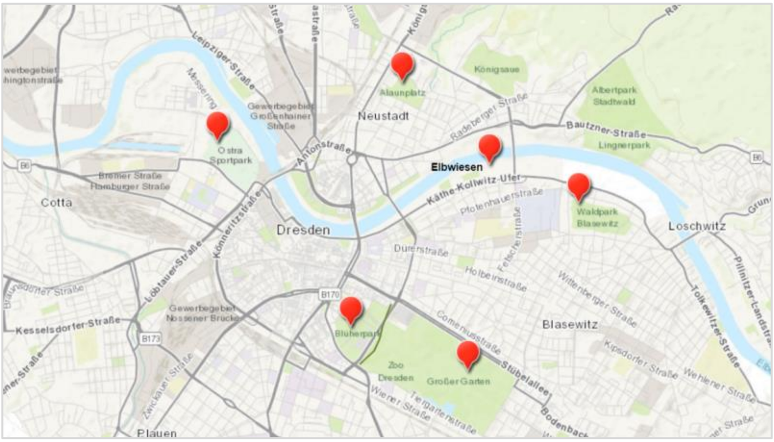


Figure 25. Positions of the parks

For this comparison, the filter was applied to the subcategory of *activities* "Outdoor Activities & Sports". First, a comparison of the number of clustered points was held to see the popularity between the years 2016-2018. Visualisations indicated that one of the most popular places for outdoor activities, sports and exercises was Sportpark Ostra. In total, 280 points could be observed in this subcategory within the boundaries of Sportpark Ostra (image no. 2 in Figure 26). After, Großer Garten seemed to be popular. Fewer points were shown on Blüher Park on the west side of Großer Garten (image no. 1 in Figure 26). Riding bicycle, football, running, volleyball and basketball were generally performed activities in Großer Garten and Sportpark Ostra. American Football was a distinct activity observed on Sportpark Ostra, differently from other parks.

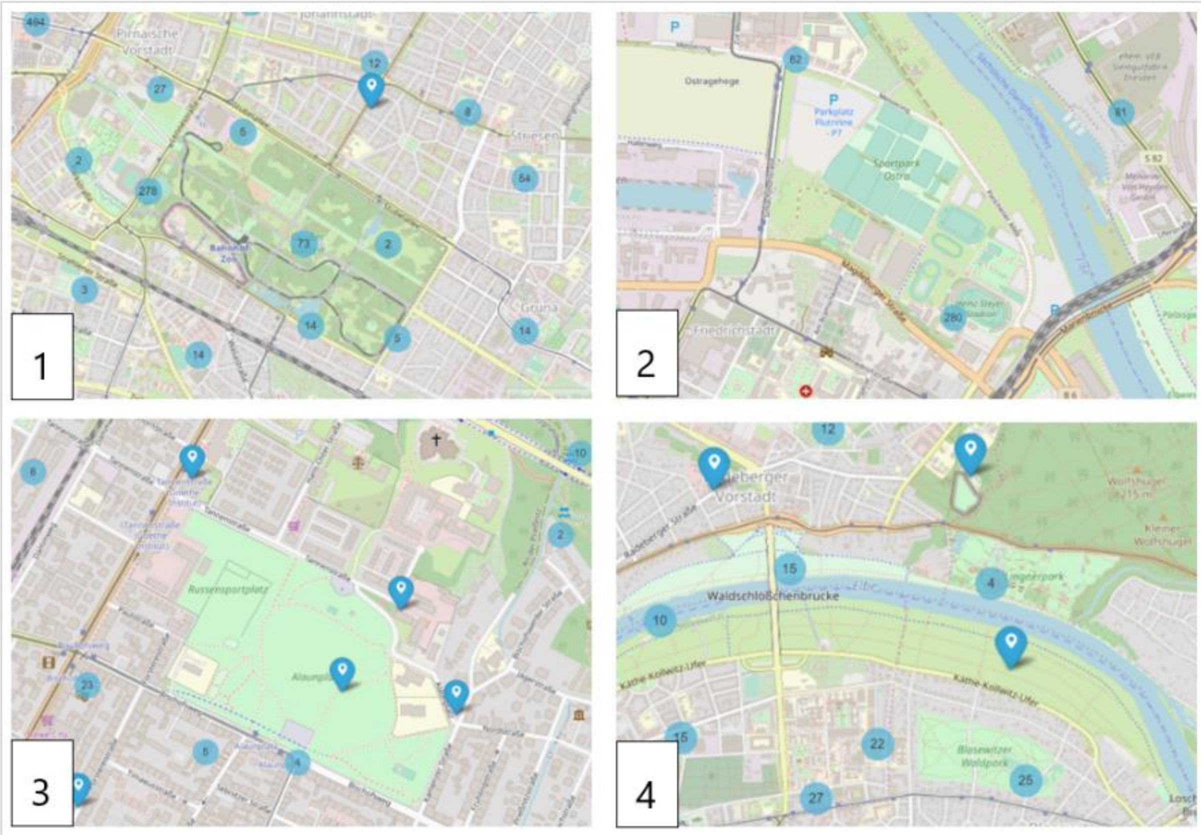


Figure 26. Filter applied in category "Outdoor Activities & Sports": (1) Großer Garten and Blüher Park, (2) Sportpark Ostra (3) Alaunpark, (4) Waldpark Blasewitz and Elbwiesen (period of 2016 - 2019)

276 points concentrated on the west side of Großer Garten on Rudolf Harbig Stadion and these posts from that location contained emojis related to football (image no. 1 in Figure 26). In this case, this significant number of clustering was ignored as it was assumed to be not related to performing the activity football but watching the performance. In Alaunpark, only a few points were classified in this subcategory (image no. 3 in Figure 26). However, the number of points increased when other subcategories of *activities* were applied, such as "Eat & Drink" and "Mental Activities & Relaxation". It may well be argued that this park was used for recreational activities like meetings, picnic and relaxing rather than sports and exercises.

There were 25 cluster points on Waldpark Blasewitz, and these activities were tennis, running and general fitness (image no. 4 in Figure 26). No clustering could be observed on Blüher Park (image no. 1 in Figure 26). It was noticeable that the inhabitants preferred to do some recreational activities at Elbwiesen along the river Elbe. The most common activity was detected as bicycle riding and running. Unlike other parks, swimming, surfing, fishing and rowing activities were noticed.

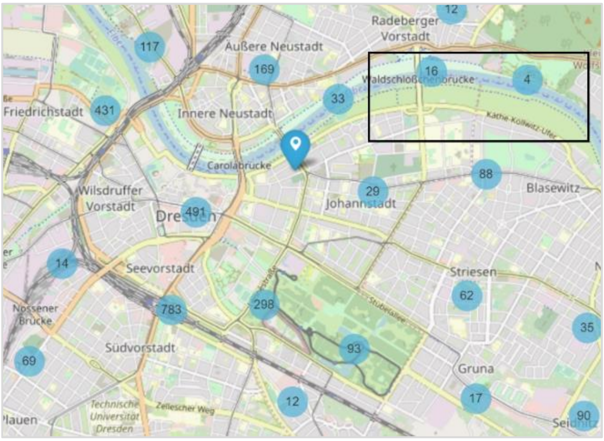


Figure 27. Elbwiesen

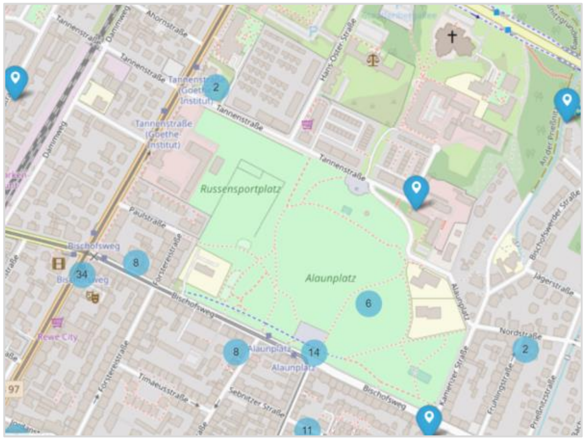


Figure 28. Filter applied in "Basic Entertainment" and "Eat & Drink" on Alaunpark

According to the visualisations, there was no place completely isolated from any recreational space and activities. It is necessary to draw attention to different activities such as swimming, fishing, surfing and rowing performed around the river Elbe. Despite this feature of Elbwiesen, the cluster points indicated that it was not one of the most preferred open areas. After further investigation of the use of this area, possible development or landscape implementation of Elbwiesen can be evaluated. These activities like swimming, fishing and surfing may be overlooked, and it may be necessary to create places for these particular activities to treat all groups of people fairly. Figure 29 illustrates the filtered visualisation of the spots where these activities were performed. Their frequency was relatively low compared to other activities, and some points were located near the Elbe. The points in the city centre (Altstadt and Neustadt) were assumed to be related to fitness studios, swimming pools.

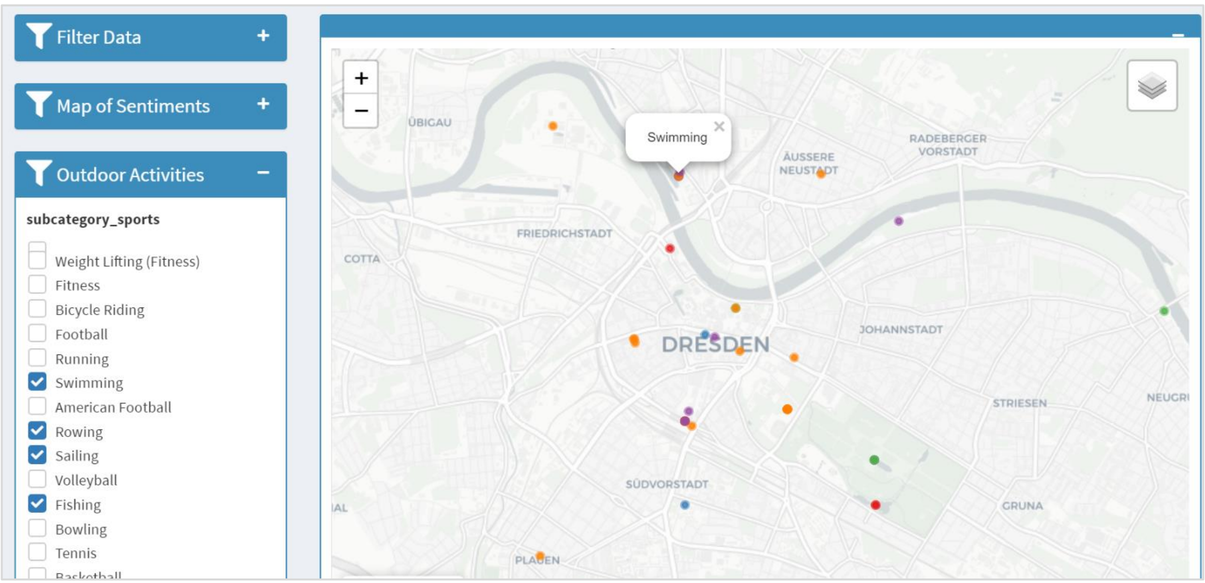


Figure 29. Swimming, rowing, sailing, fishing activity spots

One of the observations was the popularity of sports complex Sportpark Ostra. The possibility of the need for a new sports complex can be examined, and the needs of citizens must be questioned concerning this topic. In addition to this, it may be necessary to analyse the use of Blüher Park to understand why any posts were not assigned there, in "Outdoor Activities & Sports" subcategory.

The detection of temporal changes in activities was done by using the heatmap, using the date range and comparing two periods; 2013-2016 and 2016-2019 (shown in Figure 30). Growth over time could be clearly observed, but this may be the cause of the increasing popularity of social media and the increasing number of users. Nevertheless, heatmaps have proven useful, enabling users to identify the patterns.

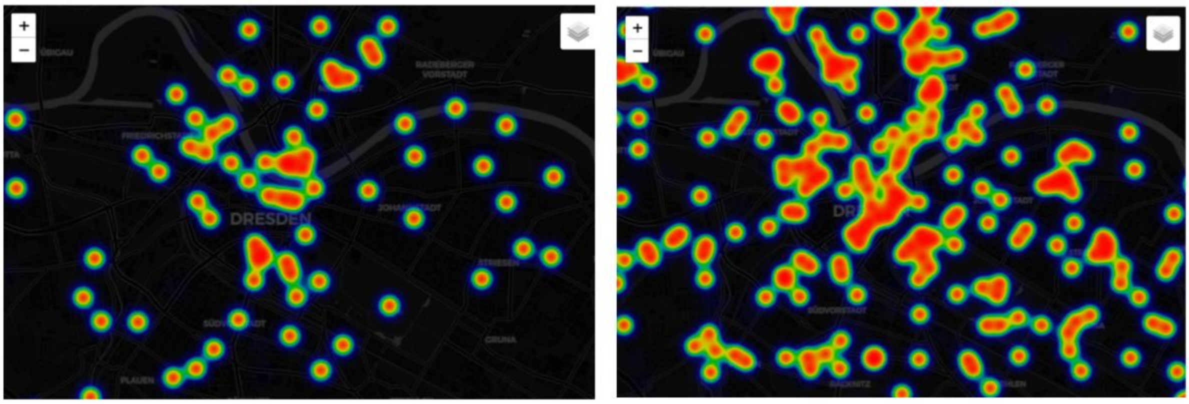


Figure 30. The heatmap created with points of "Outdoor Activities & Sports"
for the years 2013-2016 (left) and 2016-2019 (right)

4.2. Characterisation of a Neighbourhood

In the second case scenario to evaluate the use of emojis in urban and landscape planning applications, features of a neighbourhood were analysed. This was done applying the filter for *objects* category to understand spatial patterns and landmarks in the area. The neighbourhood 'Wilsdruffer Vorstadt' in Dresden was chosen because it was analysed by some projects and targeted for discussions.

The two neighbourhoods in Dresden called Wilsdruffer Vorstadt and Historic Friedrichstadt were not included in renovation actions before 2004. Those neighbourhoods were characterised by brown buildings, dwellings from various periods and, relatively poor retail structures (City of Munich and EUROCITIES, 2014). A new public renewal program started in this neighbourhood. The project called USER had chosen there as their pilot site, and surveys were conducted for effective planning decisions and to ensure public participation. USER was a project focusing on public spaces which were conducted between 2013 and 2015 by URBACT programme, which promoted sustainable urban development (URBACT, 2015).

In 2013, the chair of general economic and social geography in Dresden University of Technology surveyed for a project and asked inhabitants "Mark a public place within the map, which would be more attractive for you, if it would be modified. What changes would you suggest?" They surveyed people living in the area which covers a part of Wilsdruffer Vorstadt and a part of Historic Friedrichstadt (illustrated in Figure 31 and Figure 32).

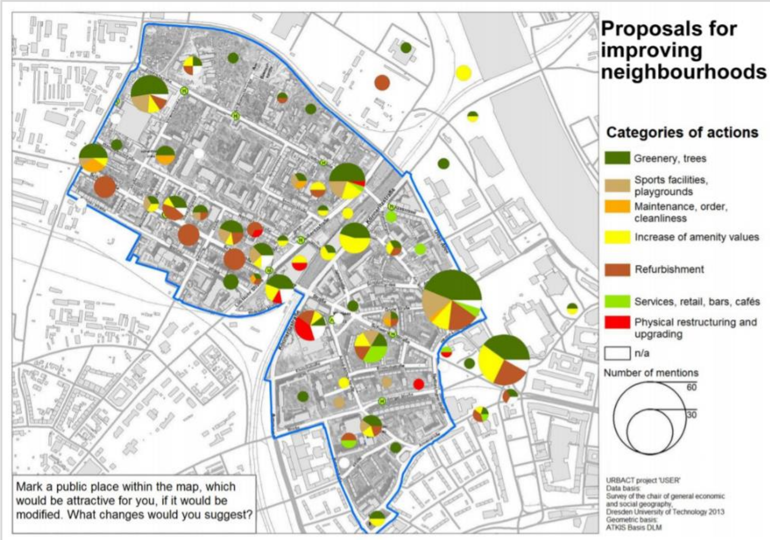


Figure 31. Assessment of public place by Inhabitants. Reprinted from Dresden in Dialog with Transformation by Chair of General Economic and Social Geography of TU Dresden, 2013.

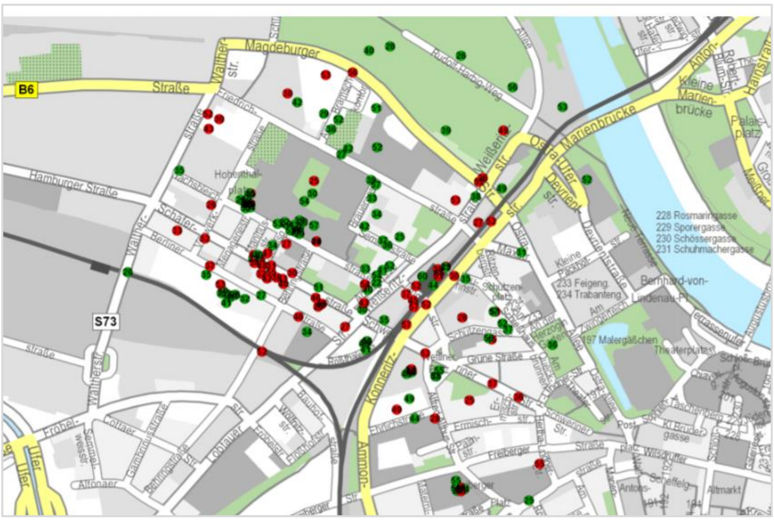


Figure 32. Comfortable and uncomfortable places according to residents' assessment. Reprinted from Dresden in Dialog with Transformation by Chair of General Economic and Social Geography of TU Dresden, 2013.

Rather than surveying inhabitants, as in the case of USER project, social media data can be utilised to obtain information about perceptions of people living in the neighbourhood and the spatial structure in the area. For this study, Wilsdruffer Vorstadt was analysed based on the interactive map visualising LBSM data based on the emoji taxonomy. In this analysis, *objects* filtering and then *sentiments* filtering was applied. Figure 33 represents screenshots for each subcategory of *objects*. As can be seen on map, 10 points for "Built-Up" subcategory, 15 points for "Commercial & Services", 49 points for "Transportation & Utilities" and 32 points for "Recreational Open Space" were assigned and shown on the map as markers and cluster points.

Figure 33. Filtering applied in category *Objects*: (1) “Built-Up”, (2) “Commercial & Services”, (3) “Transportation & Utilities”, (4) “Recreational Open Space” between 2016-2019

Remarkable numbers of points were clustered in the “Transportation & Utilities” subcategory. Most of the points were geolocated in Bahnhof Dresden Mitte and these posts included “train” (🚆) emoji. Some posts found under this filtering were given below:

- ”Dresden on the move with its stellar public transportation - Trams 🚋, buses 🚋, trains 🚆 #germany #saxony #dresden #dresdenmitte #trainstation #publictransport #tram #bus #train #groundtransportation #mural #tunnel #travel #onthemove #weekendtravelproject #AtoZinGermany”
- “A city tour of Dresden on Wilsdruffer Straße 🚌 #dvb #dresdnerverkehrsbetriebe #stad-trundfahrt #dresden #dresdenpictures #öpnvspotter“

Unlike the first case scenario concerning parks, the number of cluster points did not help to characterise this area because there were multiple posts located in only certain spots. Even though the numbers were different for each subcategory, the distribution of markers presented a similar pattern. According to the visualisation, most geolocated posts were from Dresden Mitte Bahnhof, Annenkirche, Kraftwerk Mitte, Yenidze, Hochschule für Musik Dresden, BSZ für Gastgewerbe Dresden. Table 9 demonstrates some important findings observed after the filtration process for the Wilsdruffer Vorstadt area.

Categories			
Built-Up	Commercial & Services	Transportation & Utilities	Recreational Open Space
Total Number of Points			
10	15	49	32
Emojis and Emoji Names			
○ 🏠(house building) ○ 🏢(office building)	○ ⛪(church) ○ 🏭(factory) ○ 🕌(mosque)	○ 🚲(bicycle) ○ 🚄(high-speed train) ○ 🚂(locomotive)	○ 🏖(beach with umbrella) ○ 🌄(sunrise over mountains)
Place Names			
• Dresden Mitte • Hotel Elbflorenz Dresden	• Annenkirche • Kraftwerk Mitte • Yenidze	• Freiberger Straße • Bahnhof Dresden Mitte • Kongresszentrum Dresden	• Hochschule für Musik Dresden • BSZ für Gastgewerbe Dresden • Sächsiche Schweiz

Table 9. Findings from Wilsdruffer Vorstadt area

Figure 34 shows the geovisualisations of “Negative”, “Neutral” and “Positive” sentiments in this area. Posts categorised as “Positive”, were dominating the neighbourhood. Similar to *objects* filtering, places like BSZ für Gastgewerbe Dresden, Sächsischer Landtag, Yenidze, Kongresszentrum Dresden were observed (shown in Table 10). These places were observed in all three *sentiments*. Distinctively, some cafés and bars, dance and sports schools, swimming pools were only shown as either “Neutral” or “Positive”.

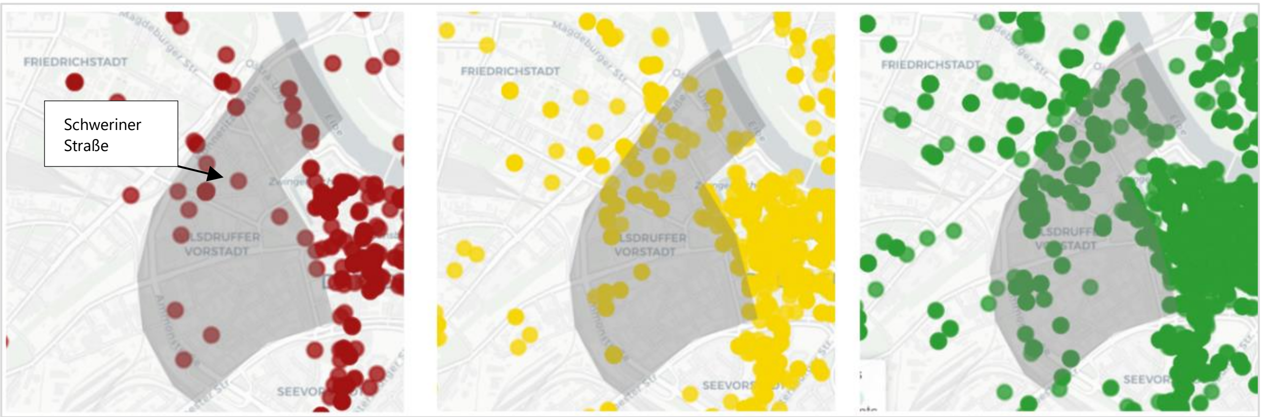


Figure 34. “Negative” (left), “Neutral” (middle), “Positive” (right)

Negative	BSZ für Gastgewerbe Dresden, Sächsischer Landtag, Yenidze, Kongresszentrum Dresden, Sternplatz
Neutral	BSZ für Gastgewerbe Dresden, Sächsischer Landtag, Yenidze, Kongresszentrum Dresden, Haus der Presse, Café Moka, Sternplatz
Positive	BSZ für Gastgewerbe Dresden, Sächsischer Landtag, Yenidze, Kongresszentrum Dresden ,Haus der Presse, Café Moka, Schwimmhalle Freiberger Platz, Staatsoperette Dresden, Cardea Pilates & Yoga, Hochschule für Musik Dresden, T1 Bistro & Café, Sternplatz

Table 10. Posts' locations categorised as "Negative", "Neutral" and "Positive"

When filtering for a*ctivities* applied, most posts sent from a location in Wilsdruffer Vorstadt neighbourhood were assigned to "Eat & Drink" and "Basic Entertainment" subcategories. It was consistent with the locations which were mostly found in *sentiments* and *objects* categories.

It is noteworthy to realise that some posts assigned to a category were unrelated to their locations. For instance, the emoji "beach with umbrella" (🏖) was mainly used in this region, and the positions of the posts did not indicate open spaces or recreational areas. A post geolocated in Hochschule für Musik Dresden was translated from German to English and as shown below:

> *"Hey! What do you feel about your holiday? Do you practice? 🎼 Are you fed up? 😩 Or do you enjoy a day off with a clear conscience? 🏖 Whatever you do, have a wonderful day ♡"*

The example of post seen above was assigned to "Mental Activity & Relaxation", "Recreational Open Space" and "Negative" subcategories based on the emoji taxonomy and because of contained emojis. Besides, the post with the place name Sächsiche Schweiz (a national park in the south-east of Dresden) was found located in Wilsdruffer Vorstadt. When the post was analysed by looking at the data table, the body post could be seen as follows:

> *"Ohhh those lovely mountain sunsets... 🌄☀🏔😍📷"*

This post states that the activity was genuinely outdoors and recreational; however, the location of the post was misleading. These reasons convey that it can be misleading to evaluate posts by only filtering categories and not considering the content of the post. A better assessment and analysis can be made by applying all filtering categories separately and considering them together. Most visited places and spatial patterns can be observed by filtering options and visualisations, yet the table should be used to see the body content and to retrieve opinions from users.

4.3. Further Ideas

Geovisualisation of emoji categorisations integrated with LBSM posts in Dresden can also help to answer the following question: Which roads are more preferred than others? This question can be answered by applying “Transportation & Utilities” subcategory filtering. The geolocated points that were assigned to “Transportation & Utilities” subcategory will illustrate the most used areas and the places where services and transportation may not be available. When new transportation routes, such as tram or bus lines need to be planned, this information would be useful to see the general picture of transportation. Additionally, applying the “Basic Entertainment” subcategory filter allows map user to see where the night-life or entertainment life in Dresden is located. The information provided from the geovisualisation is beneficial when deciding new nightline routes or aiming an overall improvement in transportation to optimise the mobility of citizens.

Last but not least, filtering options can assist in detecting communities which lack services or transportation. Ideally, the infrastructure system and services should meet the needs of all citizens, but it can be challenging to spot the locations and needs. “Built-Up” filter can be applied to locate communities, and also by exploring “Commercial & Services” and “Transportation & Utilities” subcategories, interpretation of the situation and detection of such cases would be facilitated.

4.4. Evaluation of the Case Scenarios

Parks in Dresden were characterised according to the map based on emoji usage on social media, with the help of filtering options of *activities* category. Different parks could be easily compared in terms of the number of visitors and the type of activities performed. Distinctive activities were noted, such as swimming and fishing. By the help of the heatmap, the temporal changes in “Outdoor Activities & Sports” were observed. Observation and profiling of parks contribute to the creation of citizen-centred approaches when planning landscape areas. However, some disorienting cases were observed when answering the questions to be answered in the first case scenario.

Big cluster points were observed in a stadium in Dresden called Rudolf Harbig Stadion, and this situation caused confusion and led to a question: Do the points indicate the performance itself or are they just related to watching the performance? At the same time, another confusion emerged comparing the temporal changes with the help of the heatmap: Did the sites where people perform activities expand by time or did the number of social media users increase? These questions show that further investigations and prior knowledge about the city are necessary to clarify the confusions. This was considered to be a weak point of the categorisation and geovisualisation approach.

This research also investigated the neighbourhood Wilsdruffer Vorstadt in order to learn about the features of the area and to test the interactive map usability. This neighbourhood was chosen because one study called USER (URBACT, 2015) has already conducted surveys to assess the characteristics of the district. The importance of analysing this region and the possibility of comparison created the motivation for selecting this region.

In the survey of the project, citizens often proposed improvements for green areas and developments for retails, bars and cafes were not proposed by many people (Figure 31). Filtering of *objects* category on interactive map allowed to determine and compare the following areas: "Built-Up", "Commercial & Services", "Transportation & Utilities", "Recreational Open Space". According to the results, no parks could be observed on the map, in spite of the fact that cluster points were observed in the "Recreational and Open Space" subcategory. When it was carefully observed, places like Hochschule für Musik Dresden, BSZ für Gastgewerbe Dresden and Sächsiche Schweiz were the locations of the posts. The emoji "beach with umbrella" (🏖) was assigned to "Recreational and Open Space" subcategory, but the emoji was found in a post located in Hochschule für Musik Dresden (Dresden College of Music). This proves the point that Tigwell and Flatla (2016) investigated in their paper: The emojis are used and interpreted in different ways. In addition to this problem, the names of places such as Sächsiche Schweiz that are not in the neighbourhood were also shown up in this area.

A comparison was made between the survey about overall comfort in the district (Figure 32) and the interactive map of this study using *sentiments* category filtering (Figure 34). The uncomfortable points that were stated in the survey and the points that were marked as negative sentiments on the map corresponded to each other. For example, negative points were found on the map around Schweriner Straße, where participants of the survey marked as uncomfortable places (Figure 34).

Filtering the "Recreational and Open Space" subcategory failed to evaluate parks, besides negative – neutral – positive sentiments were compacted in the same places. Therefore, no successful comparison could be made with the findings of USER project. Notwithstanding, no parks were observed on the map, which indicated that there could be a need for new recreational places, as the participants of the survey also stated (Figure 31). In addition, landmarks could be easily identified in the neighbourhood.

The web map created based on emojis can give unique ideas on issues that would take time to collect and visualise. Case studies showed that interactive map and filtering features could help characterise specific areas and give an idea about the use of the city. Emojis were used in compliance with the locations, such as "train" emoji was found around train stations, "church" emoji was found around churches. This fact was found to confirm the adopted methodology of categorisation. More importantly, it proved that analysing the use of emoji could help identify landmarks in the city. However, the map did not provide absolute accuracy and specific information about the opinions and needs of people. Despite some disadvantages and weaknesses, two of the case scenarios have demonstrated that geolocated LBSM data creates a new information source about urban and social dynamics when it is processed and interpreted thoroughly.

5. The Discussion

This chapter will firstly discuss the contributions of this research to the current knowledge. Secondly, future work suggestions to improve the current methodology will be argued together with limitations and weaknesses of the study.

5.1. Contributions to Current Research

Previous investigations implemented diverse approaches to use LBSM data in urban studies and other fields. Geo-referenced social media data was used to discover urban dynamics (Dunkel 2015; Frias-Martinez *et al.* 2012; Hasan, Zhan, and Ukkusuri 2013; Anselin and Williams 2015; Williams 2012). However, there has been an absence where emojis extracted from LBSM has been used and investigated for urban research, along with an interactive geovisualisation. Emoji usage was analysed for obtaining sentiments by scholars (Novak *et al.*, 2015; Wood and Ruder, 2016; Ayvaz and Shiha, 2017; Fernández-Gavilanes *et al.*, 2018; Hauthal, Burghardt and Dunkel, 2019) but the use of emojis was not explored to detect activity and spatial patterns. Analysing emoji usage to determine activity and spatial patterns, and sentiments for urban planning applications was not elucidated before.

This research has contributed to the current research in the following ways. Firstly, a taxonomy of emojis for urban studies was generated (demonstrated in Appendix A). This taxonomy can be used by other studies aimed at exploring a city exploiting emoji usage. In addition to this, a new attempt was made to draw the symbols in a word cloud, rather than words and letters (showed in Appendix B). Secondly, an interactive geovisualisation method was adopted to facilitate the exploration of the city through social media. Among other studies, it was the first attempt to visualise LBSM data according to the use of emoji, by creating a web map and providing filtering options. Building an interactive map was preferred as it was more explanatory than a static map. Generated categories were more meaningful to interpret when they were visualised together. As a matter of fact, this approach was proved to be useful for discovering the area of Wilsdruffer Vorstadt, where the subcategories of *objects* were applied separately and then all together, followed by *sentiments*.

5.2. Limitations and Future Work

In the case scenarios, it was observed that there was a harmony between the use of emojis and places. For example, "church" (⛪) emoji was used around the church Annenkirche, emojis like "high-speed train" (🚄) or "train" (🚆) were found around train stations. *Activities* that were shown on the map did not contradict with daily urban life. Points assigned to "Outdoor Activities & Sports" were concentrated in parks, points in "Shopping" were concentrated on shopping centres. Nevertheless, the use of emojis differs among users; the context of post and choice of emoji can be different from each other. Therefore, the geographical position of the posts did not always match the emojis.

The categorisation of *sentiments* must be approached more carefully. 75% of posts were assigned as positive; meanwhile, only 5% of posts were negative. Using social media has an effect on increasing self-esteem (Wilcox and Stephen, 2013); accordingly, users tend to look positive to others rather than sharing thoroughly honest opinions and sentiments. 75% of posts were assigned as positive, yet this does not indicate the degree of satisfaction from the places.

Privacy is also a concern when LBSM is used to understand and analyse cities. The data was retrieved from whose social media data was public, so there has been no personal interaction with participants. In this research, the data was visualised as an online interactive web map application. Particularly after integrating the table, location coordinates and posts became visible to the public. That is why stronger privacy protections are needed in future to prevent possible harms.

Section 4.4 discussed some limitations which were faced in case scenarios: Because of the nature of using social media and the emoji usage, the map was not capable of giving one hundred percent accurate information. Emojis are interpreted differently between people (Hauthal, Burghardt and Dunkel, 2019) and some factors like age or gender affect emoji usage (Lu *et al.*, 2016). Credibility and trustworthiness are still controversial topics using social media information (Moturu and Liu, 2011). For example, this study has proven that people use emojis corresponding to their activities, but it may not continuously be the case.

Another limitation was the degree of the representativeness of the data due to the complex nature of LBSM. As it was discussed in previous sections and proven by other researchers, LBSM data does not represent the entire population (Quercia *et al.*, 2013). A particular socio-demographic group may be using social media applications in Dresden. Thus, the user profile in the LBSM data can be researched in detail to draw a demographic structure of the users. In addition, this research only considered the posts containing at least one emoji. Only 18% of posts included emoji, and the geovisualisation was made considering the 18% of the whole data. Besides, locations did not always point places but larger regions. For example, in our data, approximately 14% of posts were geolocated in “Dresden, Germany”, on the coordinates 51.0416 (latitude) and 13.7333 (longitude). These being said, accounting for the biases in the model and considering the data representativeness carry great importance while using social media as a resource of information in urban and landscape planning applications.

Many posts contained more than one emojis, and this led to a confusing deduction. For example; a post included all following emojis (😤; 😎; 😏; 😧; 😏); consequently, the position of this geolocated post was assigned to both negative and positive. At the same time, this caused overlapping markers on the map that reduced the readability of the map. The main reason for having this problem was, all posts were evaluated multiple times, accordingly to contained emojis. A new methodology and approach to overcome this issue can be discovered. For instance, in such cases, sentiment analysis by text mining can make more sense than assigning a post multiple times in contradictory categories. Sentiment analysis can be also performed in LBSM data and later visualised to compare with the current map which was generated by considering the only emojis.

Applying machine learning techniques is an exciting idea when creating an emoji taxonomy. Applying a supervised text classification can be experimented to assign emojis in categories, by using the Unicode names of emojis. After creating a topic modelling of determined categories and subcategories, names of emojis can be automatically assigned to different classes.

Regarding visualisation, there remain necessary improvements. The approach for building an interactive map with filtering options was proven to be advantageous. Nonetheless, the size of symbols for clustering did not correspond with the number of clustered points. Because of the limitations of libraries, having different sizes of clustering was not possible. Another library and overall another approach could be found for creating a more explicit map. Secondly, comparing different periods would be more practical if two maps were inserted in one page, rather than changing filters on one single map.

As Rhyne, MacEachren, and Dykes (2006) stated, while digital maps have become technologically sophisticated, they still need to be based on appropriate theory and evaluated through experimental frameworks to know the effects and usability of evolving techniques. Therefore, another map technique can be tried to visualise LBSM data and compared with the current web map.

Plenty of other possible developments and improvements for the future still exist. There is a need for a finer investigation of emojis and their relation to places and activities. For example, the emoji "face savoring food" was assigned to "Eat & Drink" subcategory, and "flexed biceps" was assigned to "Outdoor Activities & Sports". These two example emojis were some of the most used emojis in LBSM data in the city of Dresden. Therefore, they made a significant impact on geovisualisation. It was not clear whether, e.g., "face savouring food" was usually used when the social media user was eating something and "flexed biceps" was generally used when doing sports or they were mostly used in other contexts. After an elaborative investigation, new emojis in categories should be added, and some emojis should be removed to prevent misleading results.

Validating the outcomes is essential to adjust the approach and improve the methodology. There are seldom empirical surveys concerning sentiments combined with a spatial reference (Hauthal, Burghardt and Dunkel, 2019), or emojis. Empirical studies can be performed regarding both emotions, emojis and spatial areas to evaluate the results. After the evaluation of empirical studies, approaches and the methodology could be improved according to the findings

6. Conclusion

Inhabitants influence the decisions of urban planners directly and having information about the daily lives, and subjective values contribute to planning decisions and practices. It is possible to observe sentiments, activities and spatial patterns in a town by traditional methods like surveys. However, it can be costly and time-consuming. In order to understand urban reality, it is necessary to use all available information. The Internet has an enormous capacity to offer information about the parks, urban areas, streets and neighbourhoods which were voluntarily published by social media users. It is essential to use this information for getting significant clues about people and places.

This paper investigated the potential of the emoji choices in social media posts to characterise the urban and landscape areas. At the beginning of the research, three questions were asked: (1) *"How to classify emojis as objects, activities, sentiments in a way that it relates to urban planning and helps to outline the features of the environments and the perception of people about these places?"*, (2) *"How to visualise social media posts geolocated in Dresden based on the emojis and taxonomy, so that it becomes an information resource for decision-makers and urban planners?", (3) "What are the possible benefits of analysing emojis in geolocated social media posts for urban and landscape planning applications to analyse a city through citizens' eyes?"*

The questions were attempted to be answered during the methodology approach, visualisation process and by ultimately assessing the case scenarios. To classify emojis, firstly subcategories of *activities, objects* and *sentiments* have been determined, and emojis were assigned to the most suitable categories. Posts were assigned to categories according to the emojis they contain. An interactive web map was chosen to visualise the data, and filtering features were added so that categorisations could be explored together in a relation. Discovering sentiments in the city was more meaningful as a supplementary category to others. It was possible to discover; e.g., which emojis in *activities* were used together with positive, negative or neutral emojis. Table of the dataset which can be filtered and sorted also contributed to further exploration of posts. The heatmap was integrated to observe the lower and higher densities of points, and a word cloud to explore emojis for each category. In order to test the potential of use, two case scenarios were held for the city of Dresden: The first one profiling the parks in Dresden, and the second one analysing a district called Wilsdruffer Vorstadt. Although the limitations exist, it was observed that characterising a city can be possible for urban and landscape urban planning applications by making use of emojis in social media.

7. References

Ackerman, C. (2019) 'Emotions and Do We Need Both?' Available at: https://positivepsychology.com/positive-negative-emotions/ (Accessed: 5 August 2019).

Anālayo, B. (2017) 'What about Neutral Feelings?', *Insight Journal*, 43, pp. 1–10.

Anderson, J. R. (1976) 'A land use and land cover classification system for use with remote sensor data', *US Government Printing Office*.

Anselin, L., & Williams, S. (2016) 'Digital neighborhoods', *Journal of Urbanism: International Research on Placemaking and Urban Sustainability*, pp. 305-328.

Ayvaz, S. and Shiha, M. O. (2017) 'The Effects of Emoji in Sentiment Analysis', *International Journal of Computer and Electrical Engineering*, 9(1), pp. 360–369. doi: 10.17706/ijcee.2017.9.1.360-369.

Bal, M. (2008) 'Visual analysis', *The SAGE Handbook of Cultural Analysis*, pp. 163–184. doi: 10.4135/9781848608443.n8.

Beeley, C. (2013) 'Web Application Development with R using Shiny', *Surveillance and Society*. doi: 10.1017/CBO9781107415324.004.

Castellà, Q. and Sutton, C. (2014) 'Word storms: Multiples of word clouds for visual comparison of documents', *Proceedings of the 23rd international conference on World wide web*.

Churches, O. *et al.* (2014) 'Emoticons in mind: An event-related potential study', *Social Neuroscience*. Psychology Press, 9(2), pp. 196–202. doi: 10.1080/17470919.2013.873737.

City of Munich and EUROCITIES (2014) 'Dresden in Dialogue about Urban Transformation', *In Dialog about Urban Transformation*.

Csikszentmihalyi, M. (2000) 'Happiness, flow, and economic equality.', *The American psychologist*. doi: 10.1037/0003-066X.55.10.1163.

Dunkel, A. (2015) 'Visualizing the perceived environment using crowdsourced photo geodata', *Landscape and Urban Planning*, 142, pp. 173–186. doi: 10.1016/j.landurbplan.2015.02.022.

Dunkel, A., Löchner, M. and Krumpe, F. (2019) 'LBSN Structure Concept' Available at: https://lbsn.vgiscience.org/concept/docs/ (Accessed: 29 August 2019).

Dykes, J., MacEachren, A. M. and Kraak, M. J. (2005) 'Exploring Geovisualization', *Elsevier*.

Einav, L. and Levin, J. (2014) 'The data revolution and economic analysis', *Innovation Policy and the Economy*. doi: 10.1086/674019.

'Emoji Version 11' (2018). Available at: https://emojipedia.org/emoji-11.0/ (Accessed: 11 May 2019).

Fainstein, S. S. (2016) 'Urban Planning', *Encyclopædia Britannica*. Available at: https://www.britannica.com/topic/urban-planning (Accessed: 20 July 2019).

Fan, W. and Gordon, M. D. (2014) 'The power of social media analytics', *Communications of the ACM*, 57(6), pp. 74–81. doi: 10.1145/2602574.

Fernández-Gavilanes, M. *et al.* (2018) 'Creating emoji lexica from unsupervised sentiment analysis of their descriptions', *Expert Systems with Applications*. doi: 10.1016/j.eswa.2018.02.043.

Frias-Martinez, V. *et al.* (2012) 'Characterizing urban landscapes using geolocated tweets', *2012 International conference on privacy, security, risk and trust and 2012 international confernece on social computing.*

Gartner Inc. (2013) 'What Is Big Data?'. Available at: https://www.gartner.com/it-glossary/big-data/ (Accessed: 19 July 2019)

Goodchild, M. F. (2007) 'Citizens as sensors: the world of volunteered geography', *GeoJournal,* pp. 211-221.

Haber, R. B. and Mcnabb, D. A. (1990) 'Visualization Idioms: A Conceptual Model for Scientific Visualization Systems', *Visualization in scientific computing*.

Hall, P. and Tewdwr-Jones, M. (2010) 'Urban and regional planning', *Routledge.*

Hasan, S., Zhan, X. and Ukkusuri, S. V. (2013) 'Understanding urban human activity and mobility patterns using large-scale location-based data from online social media', *in Proceedings of the 2nd ACM SIGKDD international workshop on urban computing.*

Hauthal, E., Burghardt, D. and Dunkel, A. (2019) 'Analyzing and Visualizing Emotional Reactions Expressed by Emojis in Location-Based Social Media', *ISPRS International Journal of Geo-Information*, 8(3), p. 113. doi: 10.3390/ijgi8030113.

Hecht, B. and Stephens, M. (2014) 'A Tale of Cities: Urban Biases in Volunteered Geographic Information', *8th International Conference on Weblogs and Social Media, ICWSM 2014*, pp. 197–205. Available at: https://www.aaai.org/ocs/index.php/ICWSM/ICWSM14/paper/viewFile/8114/8120.

Hu, X. *et al.* (2013) 'Unsupervised sentiment analysis with emotional signals', *in Proceedings of the 22nd International Conference on World Wide Web*.

Hutchison, E. D. (2014) 'Dimensions of Human Behavior: Person and Environment', *SAGE Publications*. doi: 10.1017/CBO9781107415324.004.

Joassart-Marcelli, P. (2010) 'Leveling the playing field? Urban disparities in funding for local parks and recreation in the Los Angeles region', *Environment and Planning A*. doi: 10.1068/a42198.

Kaplan, A. M. and Haenlein, M. (2010) 'Users of the world, unite! The challenges and opportunities of Social Media', *Business Horizons*. doi: 10.1016/j.bushor.2009.09.003.

Kiousis, S. (2002) 'Interactivity: A concept explication', *New Media and Society*. doi: 10.1177/146144480200400303.

Landeshauptstadt Dresden (2015) '25 Jahre Stadterneuerung Dresden im Wandel'. Available at: https://www.dresden.de/de/rathaus/aktuelles/pressemitteilungen/archiv/2017/01/pm_061.php (Accessed:10 June 2019).

Lebduska, L. (2014) 'Emoji, Emoji, What for Art Thou?', *Harlot*, 12(12). Available at: http://harlotofthearts.org/index.php/harlot/article/view/186/157 (Accessed:15 June 2019).

Liepa-Zemeša, M. and Hess, D. B. (2016) 'Effects of public perception on urban planning: evolution of an inclusive planning system during crises in Latvia', *Town Planning Review*, 87(1), pp. 71–92. doi: 10.3828/tpr.2016.5.

Liu, B. (2012) ‘Sentiment Analysis and Opinion Mining’, *Synthesis Lectures on Human Language Technologies*. doi: 10.2200/S00416ED1V01Y201204HLT016.

Liu, B. and Zhang, L. (2012) ‘A survey of opinion mining and sentiment analysis’, in *Mining Text Data*. doi: 10.1007/978-1-4614-3223-4_13.

López-Ornelas, E., Abascal-Mena, R. and Zepeda-Hernández, S. (2017) ‘Social media participation in urban planning: A new way to interact and take decisions’, *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, 42(4W3), pp. 59–64. doi: 10.5194/isprs-archives-XLII-4-W3-59-2017.

Lu, X. *et al.* (2016) ‘Learning from the Ubiquitous Language: an Empirical Analysis of Emoji Usage of Smartphone Users’, *in Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pp. 770–780.

Lynch, K. (1981) 'Good city form', *Massachusetts Institute of technology*.

MacEachren, A.M., Jaiswal, A., Robinson, A.C., Pezanowski, S., Savelyev, A., Mitra, P., Zhang, X. and Blanford, J. (2011) ‘SensePlace2: GeoTwitter analytics support for situational awareness’, *in IEEE Conference on Visual Analytics Science and Technology*, pp. 181–190. doi: 10.1109/VAST.2011.6102456.

MacEachren, A. M. and Kraak, M.-J. (2008) ‘Research Challenges in Geovisualization’, *Cartography and Geographic Information Science*, 28(1), pp. 3–12. doi: 10.1559/152304001782173970.

Metin, T. C. *et al.* (2017) ‘An inventory study on the categorization and types of recreational activities’, *International Journal of Social Science*, 59, pp. 547–561.

Mora, H. *et al.* (2018) ‘Analysis of social networking service data for smart urban planning’, *Sustainability (Switzerland)*. doi: 10.3390/su10124732.

Moturu, S. T. and Liu, H. (2011) ‘Quantifying the trustworthiness of social media content’, *Distributed and Parallel Databases*. doi: 10.1007/s10619-010-7077-0.

Murray, S. (2013) 'Interactive Data Visualization for the Web', *Journal of Chemical Information and Modeling*. doi: 10.1017/CBO9781107415324.004.

Novak, P. K. *et al.* (2015) ‘Sentiment of emojis’, *PLoS ONE*. doi: 10.1371/journal.pone.0144296.

Pam M.S., N. (2013) *No Title*, *PsychologyDictionary.org*. Available at: https://psychologydictionary.org/negative-emotion/ (Accessed: 5 August 2019).

Pang, B. and Lee, L. (2009) ‘Opinion mining and sentiment analysis’, *Computational Linguistics*. doi: 10.1162/coli.2009.35.2.311.

Qu, Z. *et al.* (2018) ‘A psychological approach to “public perception” of land-use planning: A case study of Jiangsu Province, China’, *Sustainability (Switzerland)*, pp. 1–20. doi: 10.3390/su10093056.

Quercia, D. *et al.* (2012) ‘Tracking “Gross Community Happiness” from Tweets’, *in Proceedings of the ACM 2012 conference on computer supported cooperative work*, pp. 965–968.

Quercia, D. *et al.* (2013) ‘Psychological Maps 2.0: A web engagement enterprise starting in London’, *in Proceedings of the 22Nd International Conference on World Wide Web*, (Section 3), pp. 1065–1075.

Rhyne, T. M., MacEachren, A. and Dykes, J. (2006) ‘Guest editors’ introduction: Exploring geovisualization', *IEEE Computer Graphics and Applications*. doi: 10.1109/MCG.2006.80.

Sattikar, A. A. and Kulkarni, R. V (2012) 'Natural Language Processing For Content Analysis in Social Networking', *International Journal of Engineering Inventions*.

Schiller, J. and Voisard, A. (2004) 'Location-based services', *Elsevier*.

Stefanidis, A., Crooks, A. and Radzikowski, J. (2013) 'Harvesting ambient geospatial information from social media feeds', *GeoJournal*, 78(2), pp. 319–338. doi: 10.1007/s10708-011-9438-2.

Subramanian, J. *et al.* (2019) 'Exploiting emojis for sarcasm detection', *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 11549 LNCS(July), pp. 70–80. doi: 10.1007/978-3-030-21741-9_8.

Tasse, D. and Hong, J. I. (2014) 'Using Social Media Data to Understand Cities', *in Proceedings of NSF workshop on big data and urban informatics,* pp. 64–79.

Team, R. C. (2016) 'R: A Language and Environment for Statistical Computing', *R Foundation for Statistical Computing*.

The Unicode Consortium (2019) 'The Unicode Standard, Version 12.1.0'. Mountain View, CA: The Unicode Consortium. Available at: http://www.unicode.org/versions/Unicode12.1.0/ (Accessed: 18 June 2019).

Ulrich, R. S. (1983) 'Aesthetic and affective response to natural environment', *Behavior and the natural environment,* pp. 85-125.

URBACT (2015) *USER*. Available at: https://urbact.eu/user5 (Accessed: 18 August 2019).

Vieweg, S. *et al.* (2010) 'Microblogging during two natural hazards events: What twitter may contribute to situational awareness', in *Conference on Human Factors in Computing Systems*. doi: 10.1145/1753326.1753486.

Wilcox, K. and Stephen, A. T. (2013) 'Are Close Friends the Enemy? Online Social Networks, Self-Esteem, and Self-Control', *Journal of Consumer Research*. doi: 10.1086/668794.

Williams, S. (2012) 'We are here now. Social media and the psychological city', Available at: http://weareherenow.org/about.html.

Wood, I. D. and Ruder, S. (2016) 'Emoji as Emotion Tags for Tweets', *in Proceedings of LREC 2016 Workshop, Emotion and Sentiment Analysis*, pp. 76–79. Available at: https://pdfs.semanticscholar.org/41ca/94270e160cfa51e94266e5d26979e8c40413.pdf#page=86.

Appendix A: Emoji Taxonomy

EmojiCode	Emoji Symbol	Emoji Name	Category Activity	Category Object	Category Sentiment	Subcategory Sports
U+26BD	⚽	soccer ball	Outdoor Activities & Sports			Football
U+26BE	⚾	baseball	Outdoor Activities & Sports			Baseball
U+23F8	⏸	pause button	Basic Entertainment			
U+23EF	⏯	play or pause button	Basic Entertainment			
U+25B6	▶	play button	Basic Entertainment			
U+2639	☹	frowning face			Neutral	
U+263A	☺	smiling face			Positive	
U+2708	✈	airplane		Transportation & Utilities		
U+2615	☕	hot beverage	Eat & Drink			
U+26C5	⛅	sun behind cloud	Mental Activity & Relaxation			
U+26D1	⛑	rescue workers helmet	Work			
U+26EA	⛪	church		Commercial & Services		
U+26F2	⛲	fountain		Recreational Open Space		
U+26F4	⛴	ferry		Transportation & Utilities		
U+26F5	⛵	sailboat	Outdoor Activities & Sports	Recreational Open Space		Sailing
U+26F7	⛷	skier	Outdoor Activities & Sports			
U+26F8	⛸	ice skate	Outdoor Activities & Sports			
U+26F9	⛹	person bouncing ball	Outdoor Activities & Sports			Basketball
U+26FA	⛺	tent		Recreational Open Space		
U+26FD	⛽	fuel pump		Transportation & Utilities		
U+1F23A	🈺	Japanese 'open for business' button	Work			
U+1F303	🌃	night with stars	Mental Activity & Relaxation			
U+1F304	🌄	sunrise over mountains	Mental Activity & Relaxation	Recreational Open Space		
U+1F305	🌅	sunrise	Mental Activity & Relaxation	Recreational Open Space		
U+1F306	🌆	cityscape at dusk	Mental Activity & Relaxation	Recreational Open Space		
U+1F307	🌇	sunset	Mental Activity & Relaxation	Recreational Open Space		
U+1F309	🌉	bridge at night	Mental Activity & Relaxation			
U+1F324	🌤	sun behind small cloud	Mental Activity & Relaxation			
U+1F325	🌥	sun behind large cloud	Mental Activity & Relaxation			
U+1F326	🌦	sun behind rain cloud	Mental Activity & Relaxation			
U+1F32D	🌭	hot dog	Eat & Drink			
U+1F32E	🌮	taco	Eat & Drink			
U+1F32F	🌯	burrito	Eat & Drink			
U+1F330	🌰	chestnut	Eat & Drink			
U+1F336	🌶	hot pepper	Eat & Drink			

U+1F33D	🌽	ear of corn	Eat & Drink			
U+1F33E	🌾	sheaf of rice	Eat & Drink			
U+1F344	🍄	mushroom	Eat & Drink			
U+1F345	🍅	tomato	Eat & Drink			
U+1F347	🍇	grapes	Eat & Drink			
U+1F348	🍈	melon	Eat & Drink			
U+1F349	🍉	watermelon	Eat & Drink			
U+1F34A	🍊	tangerine	Eat & Drink			
U+1F34B	🍋	lemon	Eat & Drink			
U+1F34C	🍌	banana	Eat & Drink			
U+1F34D	🍍	pineapple	Eat & Drink			
U+1F34E	🍎	red apple	Eat & Drink			
U+1F34F	🍏	green apple	Eat & Drink			
U+1F350	🍐	pear	Eat & Drink			
U+1F351	🍑	peach	Eat & Drink			
U+1F352	🍒	cherries	Eat & Drink			
U+1F353	🍓	strawberry	Eat & Drink			
U+1F354	🍔	hamburger	Eat & Drink			
U+1F355	🍕	pizza	Eat & Drink			
U+1F356	🍖	meat on bone	Eat & Drink			
U+1F357	🍗	poultry leg	Eat & Drink			
U+1F358	🍘	rice cracker	Eat & Drink			
U+1F359	🍙	rice ball	Eat & Drink			
U+1F35A	🍚	cooked rice	Eat & Drink			
U+1F35B	🍛	curry rice	Eat & Drink			
U+1F35C	🍜	steaming bowl	Eat & Drink			
U+1F35D	🍝	spaghetti	Eat & Drink			
U+1F35E	🍞	bread	Eat & Drink			
U+1F35F	🍟	french fries	Eat & Drink			
U+1F360	🍠	roasted sweet potato	Eat & Drink			
U+1F361	🍡	dango	Eat & Drink			
U+1F363	🍣	sushi	Eat & Drink			
U+1F364	🍤	fried shrimp	Eat & Drink			
U+1F365	🍥	fish cake with swirl	Eat & Drink			
U+1F366	🍦	soft ice cream	Eat & Drink			
U+1F367	🍧	shaved ice	Eat & Drink			
U+1F368	🍨	ice cream	Eat & Drink			
U+1F369	🍩	doughnut	Eat & Drink			
U+1F36A	🍪	cookie	Eat & Drink			
U+1F36B	🍫	chocolate bar	Eat & Drink			
U+1F36C	🍬	candy	Eat & Drink			
U+1F36D	🍭	lollipop	Eat & Drink			

U+1F36E	🍮	custard	Eat & Drink			
U+1F36F	🍯	honey pot	Eat & Drink			
U+1F370	🍰	shortcake	Eat & Drink			
U+1F371	🍱	bento box	Eat & Drink			
U+1F372	🍲	pot of food	Eat & Drink			
U+1F373	🍳	cooking	Eat & Drink			
U+1F374	🍴	fork and knife	Eat & Drink			
U+1F375	🍵	teacup without handle	Eat & Drink			
U+1F376	🍶	sake	Eat & Drink			
U+1F377	🍷	wine glass	Eat & Drink			
U+1F378	🍸	cocktail glass	Eat & Drink			
U+1F379	🍹	tropical drink	Eat & Drink			
U+1F37A	🍺	beer mug	Mental Activity & Relaxation			
U+1F37B	🍻	clinking beer mugs	Eat & Drink			
U+1F37D	🍽	fork and knife with plate	Eat & Drink			
U+1F37E	🍾	bottle with popping cork	Eat & Drink			
U+1F37F	🍿	popcorn	Basic Entertainment			
U+1F382	🎂	birthday cake	Eat & Drink			
U+1F399	🎙	studio microphone	Basic Entertainment			
U+1F39E	🎞	film frames	Basic Entertainment			
U+1F39F	🎟	admission tickets	Basic Entertainment			
U+1F3A0	🎠	carousel horse		Recreational Open Space		
U+1F3A2	🎢	roller coaster	Basic Entertainment			
U+1F3A3	🎣	fishing pole	Outdoor Activities & Sports			Fishing
U+1F3A4	🎤	microphone	Basic Entertainment			
U+1F3A5	🎥	movie camera	Basic Entertainment			
U+1F3A6	🎦	cinema	Basic Entertainment			
U+1F3A7	🎧	headphone	Basic Entertainment			
U+1F3A8	🎨	artist palette	Basic Entertainment			
U+1F3AB	🎫	ticket	Basic Entertainment			
U+1F3AD	🎭	performing arts	Basic Entertainment			
U+1F3AE	🎮	video game	Basic Entertainment			
U+1F3B1	🎱	pool 8 ball	Basic Entertainment			
U+1F3B3	🎳	bowling	Outdoor Activities & Sports			Bowling
U+1F3B4	🎴	flower playing cards	Basic Entertainment			
U+1F3B5	🎵	musical note	Mental Activity & Relaxation			
U+1F3B6	🎶	musical notes	Mental Activity & Relaxation			
U+1F3B8	🎸	guitar	Basic Entertainment			
U+1F3B9	🎹	musical keyboard	Mental Activity & Relaxation			
U+1F3BC	🎼	musical score	Mental Activity & Relaxation			
U+1F3BD	🎽	running shirt	Outdoor Activities & Sports			Running
U+1F3BE	🎾	tennis	Outdoor Activities & Sports			Tennis

U+1F3BF	🎿	skis	Outdoor Activities & Sports			
U+1F3C0	🏀	basketball	Outdoor Activities & Sports			Basketball
U+1F3C2	🏂	snowboarder	Outdoor Activities & Sports			
U+1F3C3	🏃	person running	Outdoor Activities & Sports			Running
U+1F3C4	🏄	person surfing	Outdoor Activities & Sports			
U+1F3C5	🏅	sports medal	Outdoor Activities & Sports			
U+1F3C7	🏇	horse racing	Outdoor Activities & Sports			
U+1F3C8	🏈	american football	Outdoor Activities & Sports			American Football
U+1F3C9	🏉	rugby football	Outdoor Activities & Sports			Rugby
U+1F3CA	🏊	person swimming	Outdoor Activities & Sports			Swimming
U+1F3CB	🏋	person lifting weights	Outdoor Activities & Sports			Weight Lifting (Fitness)
U+1F3CC	🏌	person golfing	Outdoor Activities & Sports			Golf
U+1F3CD	🏍	motorcycle		Transportation & Utilities		
U+1F3D0	🏐	volleyball	Outdoor Activities & Sports			Volleyball
U+1F3D1	🏑	field hockey	Outdoor Activities & Sports			Hockey
U+1F3D2	🏒	ice hockey	Outdoor Activities & Sports			Hockey
U+1F3D5	🏕	camping		Recreational Open Space		
U+1F3D6	🏖	beach with umbrella	Mental Activity & Relaxation	Recreational Open Space		
U+1F3D7	🏗	building construction		Built-Up		
U+1F3D8	🏘	houses		Built-Up		
U+1F3D9	🏙	cityscape	Mental Activity & Relaxation	Recreational Open Space		
U+1F3DA	🏚	derelict house		Built-Up		
U+1F3DB	🏛	classical building		Built-Up		
U+1F3DE	🏞	national park		Recreational Open Space		
U+1F3DF	🏟	stadium	Basic Entertainment	Built-Up		
U+1F3E0	🏠	house		Built-Up		
U+1F3E1	🏡	house with garden		Built-Up		
U+1F3E2	🏢	office building		Built-Up		
U+1F3E5	🏥	hospital		Commercial & Services		
U+1F3E6	🏦	bank		Commercial & Services		
U+1F3E8	🏨	hotel		Commercial & Services		
U+1F3E9	🏩	love hotel		Commercial & Services		
U+1F3EA	🏪	convenience store	Shopping	Commercial & Services		
U+1F3EB	🏫	school		Commercial & Services		
U+1F3EC	🏬	department store	Shopping	Commercial & Services		
U+1F3ED	🏭	factory		Commercial & Services		
U+1F3F0	🏰	castle		Built-Up		
U+1F3F8	🏸	badminton	Outdoor Activities & Sports			Badminton
U+1F454	👔	necktie	Work			
U+1F459	👙	bikini	Mental Activity & Relaxation			
U+1F45F	👟	running shoe	Outdoor Activities & Sports			Running
U+1F477	👷	construction worker	Work	Built-Up		

U+1F47F	👿	angry face with horns			Negative	
U+1F483	💃	woman dancing	Basic Entertainment			
U+1F4AA	💪	flexed biceps	Outdoor Activities & Sports			Fitness
U+1F4B3	💳	credit card	Shopping	Commercial & Services		
U+1F4BB	💻	laptop computer	Work			
U+1F4BD	💽	computer disk	Work			
U+1F4C1	📁	file folder	Work			
U+1F4C2	📂	open file folder	Work			
U+1F4C7	📇	card index	Work			
U+1F4D3	📓	notebook	Mental Activity & Relaxation			
U+1F4D4	📔	notebook with decorative cover	Mental Activity & Relaxation			
U+1F4D5	📕	closed book	Mental Activity & Relaxation			
U+1F4D6	📖	open book	Mental Activity & Relaxation			
U+1F4D7	📗	green book	Mental Activity & Relaxation			
U+1F4D8	📘	blue book	Mental Activity & Relaxation			
U+1F4D9	📙	orange book	Mental Activity & Relaxation			
U+1F4DA	📚	books	Mental Activity & Relaxation			
U+1F4F7	📷	camera	Basic Entertainment			
U+1F4F8	📸	camera with flash	Basic Entertainment			
U+1F4F9	📹	video camera	Basic Entertainment			
U+1F4FA	📺	television	Basic Entertainment			
U+1F4FB	📻	radio	Basic Entertainment			
U+1F4FD	📽	film projector	Basic Entertainment			
U+1F518	🔘	radio button	Basic Entertainment			
U+1F52A	🔪	kitchen knife	Eat & Drink			
U+1F54C	🕌	mosque		Commercial & Services		
U+1F54D	🕍	synagogue		Commercial & Services		
U+1F579	🕹	joystick	Basic Entertainment			
U+1F57A	🕺	man dancing	Basic Entertainment			
U+1F58C	🖌	paintbrush	Basic Entertainment			
U+1F590	🖐	hand with fingers splayed	Basic Entertainment			
U+1F5A5	🖥	desktop computer	Work			
U+1F5A8	🖨	printer	Work			
U+1F5B1	🖱	computer mouse	Work			
U+1F5C2	🗂	card index dividers	Work			
U+1F5C4	🗄	file cabinet	Work			
U+1F600	😀	grinning face			Positive	
U+1F601	😁	beaming face with smiling eyes			Positive	
U+1F602	😂	face with tears of joy			Neutral	
U+1F603	😃	grinning face with big eyes			Positive	
U+1F604	😄	grinning face with smiling eyes			Positive	
U+1F605	😅	grinning face with sweat			Neutral	

U+1F606	😆	grinning squinting face			Neutral	
U+1F607	😇	smiling face with halo			Positive	
U+1F608	😈	smiling face with horns			Neutral	
U+1F609	😉	winking face			Positive	
U+1F60A	😊	smiling face with smiling eyes			Positive	
U+1F60B	😋	face savoring food	Eat & Drink		Positive	
U+1F60C	😌	relieved face			Positive	
U+1F60D	😍	smiling face with heart-eyes			Positive	
U+1F60E	😎	smiling face with sunglasses			Positive	
U+1F60F	😏	smirking face			Neutral	
U+1F610	😐	neutral face			Negative	
U+1F611	😑	expressionless face			Negative	
U+1F612	😒	unamused face			Negative	
U+1F613	😓	downcast face with sweat			Negative	
U+1F614	😔	pensive face			Negative	
U+1F616	😖	confounded face			Negative	
U+1F617	😗	kissing face			Positive	
U+1F618	😘	face blowing a kiss			Positive	
U+1F619	😙	kissing face with smiling eyes			Positive	
U+1F61A	😚	kissing face with closed eyes			Positive	
U+1F61B	😛	face with tongue			Positive	
U+1F61C	😜	winking face with tongue			Positive	
U+1F61D	😝	squinting face with tongue			Positive	
U+1F61E	😞	disappointed face			Negative	
U+1F620	😠	angry face			Negative	
U+1F621	😡	pouting face			Negative	
U+1F622	😢	crying face			Neutral	
U+1F623	😣	persevering face			Negative	
U+1F624	😤	face with steam from nose			Negative	
U+1F625	😥	sad but relieved face			Neutral	
U+1F626	😦	frowning face with open mouth			Negative	
U+1F627	😧	anguished face			Neutral	
U+1F628	😨	fearful face			Negative	
U+1F629	😩	weary face			Negative	
U+1F62A	😪	sleepy face			Neutral	
U+1F62B	😫	tired face			Negative	
U+1F62C	😬	grimacing face			Neutral	
U+1F62D	😭	loudly crying face			Negative	
U+1F62E	😮	face with open mouth			Neutral	
U+1F62F	😯	hushed face			Neutral	
U+1F630	😰	anxious face with sweat			Negative	
U+1F631	😱	face screaming in fear			Neutral	

U+1F632	😲	astonished face			Neutral	
U+1F633	😳	flushed face			Neutral	
U+1F634	😴	sleeping face			Neutral	
U+1F635	😵	dizzy face			Neutral	
U+1F636	😶	face without mouth			Negative	
U+1F637	😷	face with medical mask			Negative	
U+1F641	🙁	slightly frowning face			Neutral	
U+1F642	🙂	slightly smiling face			Positive	
U+1F643	🙃	upside-down face			Positive	
U+1F644	🙄	face with rolling eyes			Negative	
U+1F681	🚁	helicopter		Transportation & Utilities		
U+1F682	🚂	locomotive		Transportation & Utilities		
U+1F683	🚃	railway car		Transportation & Utilities		
U+1F684	🚄	high-speed train		Transportation & Utilities		
U+1F685	🚅	bullet train		Transportation & Utilities		
U+1F686	🚆	train		Transportation & Utilities		
U+1F687	🚇	metro		Transportation & Utilities		
U+1F688	🚈	light rail		Transportation & Utilities		
U+1F689	🚉	station		Transportation & Utilities		
U+1F68A	🚊	tram		Transportation & Utilities		
U+1F68B	🚋	tram car		Transportation & Utilities		
U+1F68C	🚌	bus		Transportation & Utilities		
U+1F68D	🚍	oncoming bus		Transportation & Utilities		
U+1F68E	🚎	trolleybus		Transportation & Utilities		
U+1F68F	🚏	bus stop		Transportation & Utilities		
U+1F690	🚐	minibus		Transportation & Utilities		
U+1F694	🚔	oncoming police car		Transportation & Utilities		
U+1F695	🚕	taxi		Transportation & Utilities		
U+1F696	🚖	oncoming taxi		Transportation & Utilities		
U+1F697	🚗	automobile		Transportation & Utilities		
U+1F698	🚘	oncoming automobile		Transportation & Utilities		
U+1F69D	🚝	monorail		Transportation & Utilities		
U+1F69E	🚞	mountain railway		Transportation & Utilities		
U+1F69F	🚟	suspension railway		Transportation & Utilities		
U+1F6A0	🚠	mountain cableway		Transportation & Utilities		
U+1F6A1	🚡	aerial tramway		Transportation & Utilities		
U+1F6A2	🚢	ship		Transportation & Utilities		
U+1F6A3	🚣	person rowing boat	Outdoor Activities & Sports	Transportation & Utilities		Rowing
U+1F6A4	🚤	speedboat	Outdoor Activities & Sports	Transportation & Utilities		
U+1F6A5	🚥	horizontal traffic light		Transportation & Utilities		
U+1F6A6	🚦	vertical traffic light		Transportation & Utilities		
U+1F6B2	🚲	bicycle	Outdoor Activities & Sports	Transportation & Utilities		Bicycle Riding

U+1F6B3	🚳	no bicycles	Outdoor Activities & Sports	Transportation & Utilities		
U+1F6B4	🚴	person biking		Transportation & Utilities		
U+1F6B5	🚵	person mountain biking	Outdoor Activities & Sports	Transportation & Utilities		Bicycle Riding
U+1F6B6	🚶	person walking	Mental Activity & Relaxation			
U+1F6B7	🚷	no pedestrians		Transportation & Utilities		
U+1F6B8	🚸	children crossing		Transportation & Utilities		
U+1F6C2	🛂	passport control		Transportation & Utilities		
U+1F6C3	🛃	customs		Transportation & Utilities		
U+1F6C4	🛄	baggage claim		Transportation & Utilities		
U+1F6CD	🛍	shopping bags	Shopping	Commercial & Services		
U+1F6D0	🛐	place of worship		Commercial & Services		
U+1F6D2	🛒	shopping cart	Shopping	Commercial & Services		
U+1F6E3	🛣	motorway		Transportation & Utilities		
U+1F6E4	🛤	railway track		Transportation & Utilities		
U+1F6E5	🛥	motor boat	Outdoor Activities & Sports	Transportation & Utilities		
U+1F6E9	🛩	small airplane		Transportation & Utilities		
U+1F6EB	🛫	airplane departure		Transportation & Utilities		
U+1F6EC	🛬	airplane arrival		Transportation & Utilities		
U+1F6F3	🛳	passenger ship		Transportation & Utilities		
U+1F6F4	🛴	kick scooter		Transportation & Utilities		
U+1F6F5	🛵	motor scooter		Transportation & Utilities		
U+1F6F6	🛶	canoe	Outdoor Activities & Sports			Canoe
U+1F910	🤐	zipper-mouth face			Negative	
U+1F914	🤔	thinking face			Negative	
U+1F917	🤗	hugging face			Negative	
U+1F922	🤢	nauseated face			Negative	
U+1F923	🤣	rolling on the floor laughing			Neutral	
U+1F928	🤨	face with raised eyebrow			Negative	
U+1F92A	🤪	zany face			Positive	
U+1F92B	🤫	shushing face			Negative	
U+1F92D	🤭	face with hand over mouth			Negative	
U+1F92E	🤮	face vomiting			Negative	
U+1F92F	🤯	exploding head			Neutral	
U+1F942	🥂	clinking glasses	Eat & Drink			
U+1F943	🥃	tumbler glass	Eat & Drink			
U+1F944	🥄	spoon	Eat & Drink			
U+1F950	🥐	croissant	Eat & Drink			
U+1F951	🥑	avocado	Eat & Drink			
U+1F957	🥗	green salad	Eat & Drink			
U+1F958	🥘	shallow pan of food	Eat & Drink			
U+1F959	🥙	stuffed flatbread	Eat & Drink			
U+1F95B	🥛	glass of milk	Eat & Drink			

U+1F95C	🥜	peanuts	Eat & Drink			
U+1F95E	🥞	pancakes	Eat & Drink			
U+1F963	🥣	bowl with spoon	Eat & Drink			
U+1F965	🥥	coconut	Eat & Drink			
U+1F968	🥨	pretzel	Eat & Drink			
U+1F969	🥩	cut of meat	Eat & Drink			
U+1F9C0	🧀	cheese wedge	Eat & Drink			
U+1F9D7	🧗	person climbing	Outdoor Activities & Sports			

Appendix B: Wordcloud of Emojis in *(1) Objects, (2) Activities, (3) Sentiments* Categories

1

2

3