TECHNISCHE UNIVERSITÄT DRESDEN

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

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Outline

1. Introduction
2. Related Work
3. Methodology and Analysis of the Results
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Introduction

- Location-Based Social Media (LBSM) has become popular in a range of fields, including urban planning studies.
- 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.
- The adoption of emojis gives researchers opportunities to conduct studies which had limitations formerly.
- Geolocated social media data and emojis can be used to explore and understand the city by finding an approach to transform this data into information.

Introduction
Research Objectives

- ***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.*

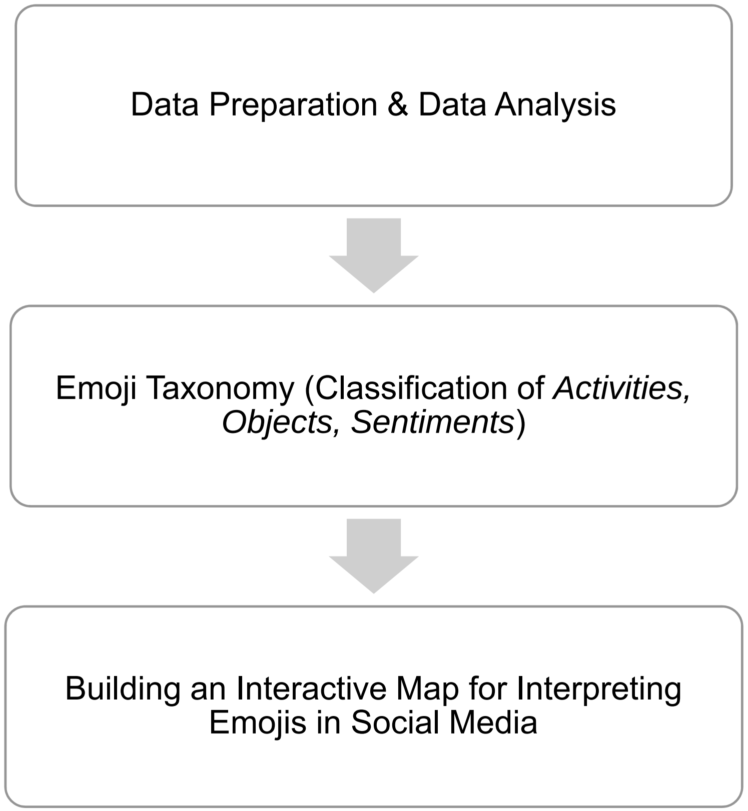
Related Work

- Researches utilised social media to study the perception of citizens towards a city. The expert investigated a range of socio-economic classes by analysing Facebook and Foursquare check-in locations and densities (Williams, 2012).
- Scholars performed sentiment analysis using Twitter data and explored the association between sentiments and socio-economic well-being in the city London (Quercia et al., 2012).
- LBSM has been analysed to determine activity types and mobility patterns in a city. A study investigated urban human mobility by portraying aggregated and individual activity patterns and visualised as a virtual grid reference city map (Hasan, Zhan and Ukkusuri, 2013).
- Dunkel (2015) experimented different visualisation techniques of crowdsourced photo geodata from Flickr to provide perceptual features of landscapes.

Related Work

- Novak, Smailović, Sluban and Mozetić (2015) created a sentiment lexicon of emojis, using tweets that included emoji. 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.
- Ayvaz and Shiha (2017) studied the usage of emojis in events related to positive and negative feelings. Researchers firstly applied a sentiment analysis only considering words and than they repeated that taking into account the emoji. They pointed out that considering emojis in sentiment analysis improves the sentiment scores.
- Scholars investigated reactions of people towards events based on LBSM posts and use of emojis (Hauthal, Burghardt and Dunkel, 2019). According to the results, sentiment analysis combining hashtags with emojis reflected better results than only hashtag-based evaluations.

Methodology and Analysis of the Results



The Workflow

Methodology and Analysis of the Results

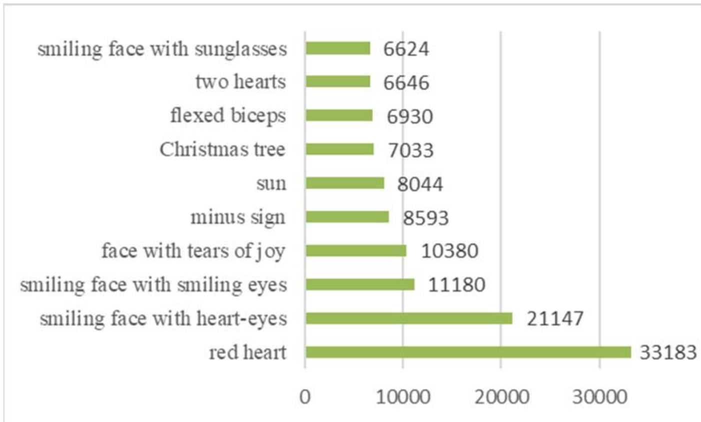
Data Preparation, Analysis and Results

- The data consisted 1,073,095 posts, which were posted between the years 2007 – 2018.
- Posts which do not include any emoji were removed (the remaining posts were 18% of total dataset).
- Individual emojis were assigned to separate rows.

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

lat	lng	post_id	post_publis	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

- Emoji usage in LBSM data in Dresden was analysed.

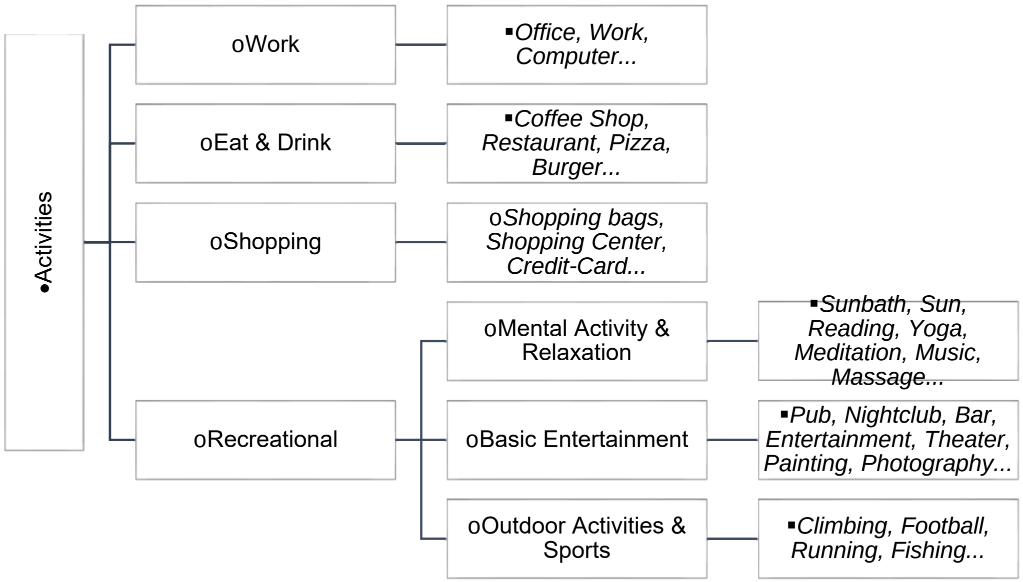


Most used emojis in LBSM data

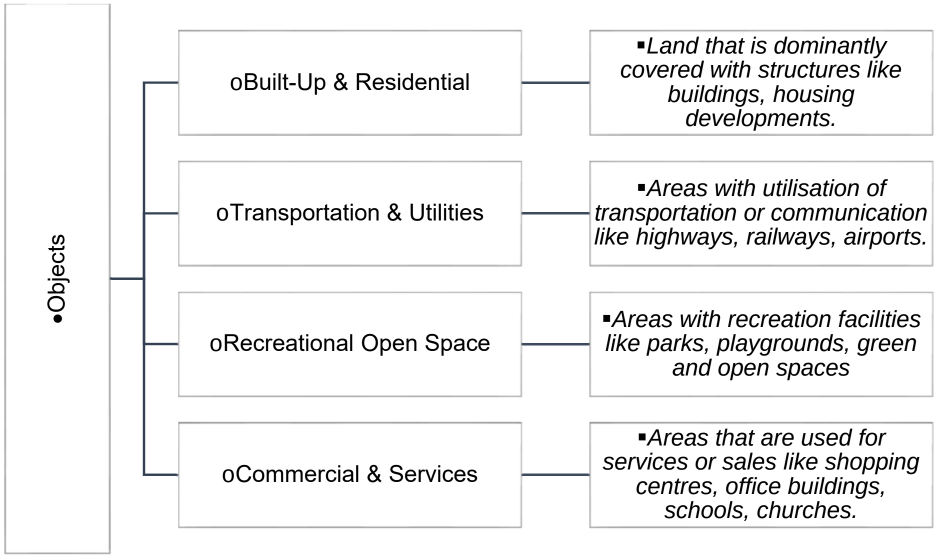
Methodology and Analysis of the Results

Emoji Taxonomy

1. Classification of Activities, Objects, Sentiments



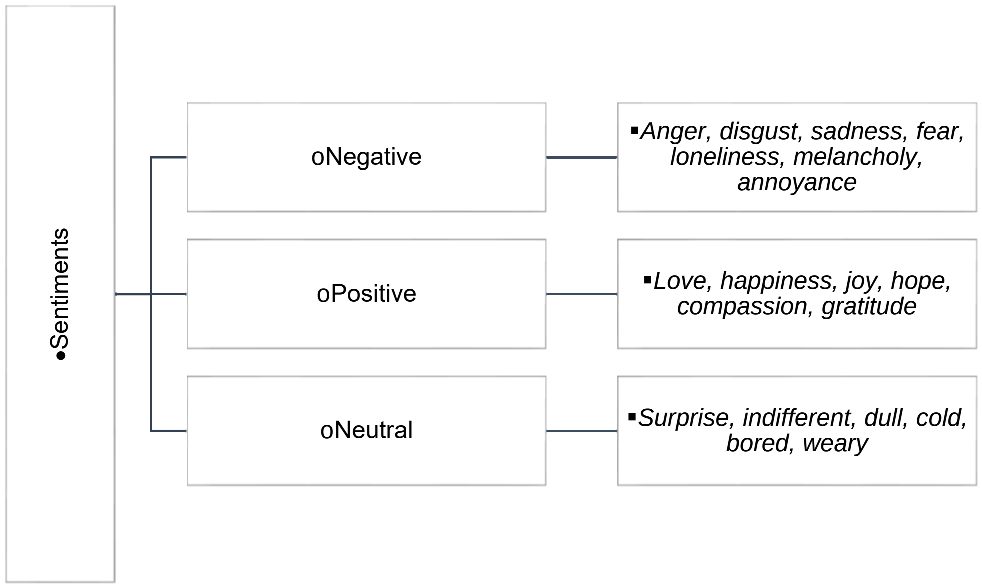
Researches of Metin et al. (2017) and Hasan, Zhan and Ukkusuri (2013) were taken as reference in the classification and determining the keywords.



Research of Anderson (1976) was taken as reference in the classification and determining the keywords.

Methodology and Analysis of the Results
Emoji Taxonomy

1. Classification of Activities, Objects, Sentiments



Researches Csikszentmihalyi (2000), Ackerman (2019), Anālayo (2017) were taken as reference in the classification and determining the keywords.

Emoji Taxonomy

2. Assigning Emojis into Activities, Objects, Sentiments

For Activities and Objects

I. Defining the keywords

II. Matching keywords

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

=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

Matching keywords with emoji names

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

Keywords for categories

III. Assignment of posts to categories based on the emojis they contain

Emoji Taxonomy

2. Assigning Emojis into Activities, Objects, Sentiments

For Sentiments

I. Selection of emojis

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

II. Ranking emojis with the help of “Emoji Sentiment Ranking v1.0” (Novak et al., 2015).

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

III. Dividing emoji list equally into three sections according to their ranking and assigning in subcategories.

Emoji Taxonomy

Emoji Name	Emojis
eat & drink	
face savouring food	😋
outdoor activities & sports	
flexed biceps	💪
basic entertainment	
camera	📷
mental activity, relaxation	
musical notes	🎶
shopping	
shopping cart	🛒
work	
laptop computer	💻

Activities Subcategories and Example of Assigned Emojis

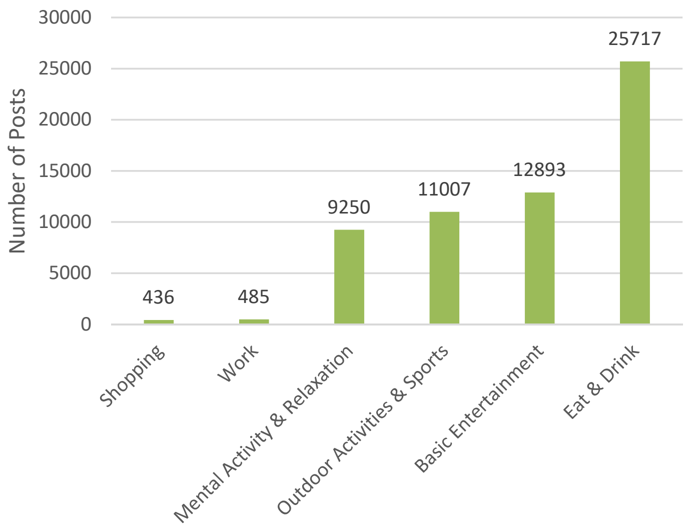
Emoji Name	Emojis
built-up & residential	
church	⛪
commercial & services	
bus	🚌
recreational & open space	
national park	🏞
transportation & utilities	
bicycle	🚲

Objects Subcategories and Example of Assigned Emojis

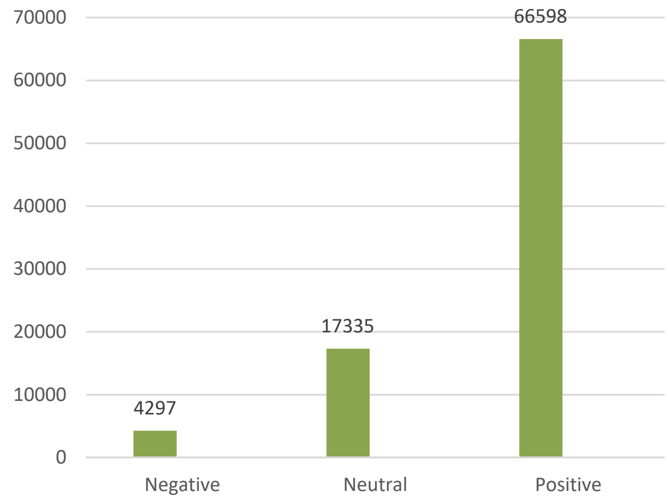
Emoji Name	Emoji
negative	
loudly crying face	😭
neutral	
smirking face	😏
positive	
smiling face with sunglasses	😎

Sentiments Subcategories and Example of Assigned Emojis

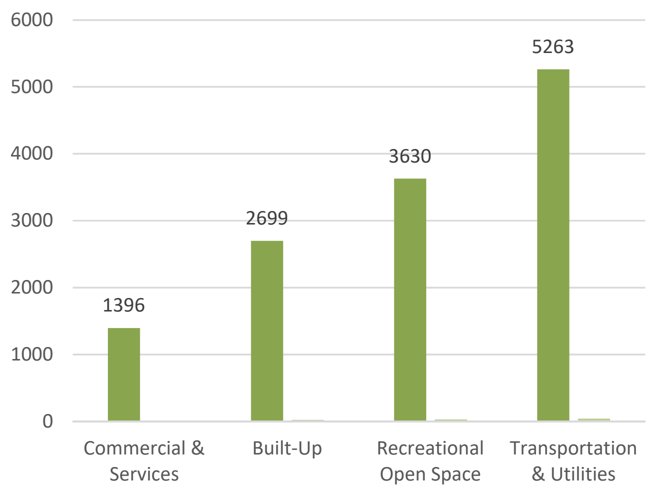
Emoji Taxonomy



Count of posts in activities category



Count of posts in sentiments category



Count of posts in objects category

Methodology and Analysis of the Results
Geovisualisation of Emojis in LBSM Posts in Dresden

- 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 map for this research was created in RStudio *Leaflet* library was used and integrated into a *Shiny* web application.
- A heatmap and Wordcloud were integrated into the web map application.

Map | Heatmap | Emoji Categorization and Wordcloud

Filter Data +

Map of Sentiments +

Outdoor Activities +

About −

This map was built using Location Based Social Media data from Dresden. Posts are classified and visualised as different categories in activities, objects and sentiments. This map was generated to assess subjective value in cities, for urban and landscape planning applications by analysing emoji use in social media data. To explore the data, check 'Data Table' below the map and you can discover the posts via ID numbers (shown on pop-ups). 'Heatmap' visualises the pattern of … 'Wordcloud' illustrates the emojis and their

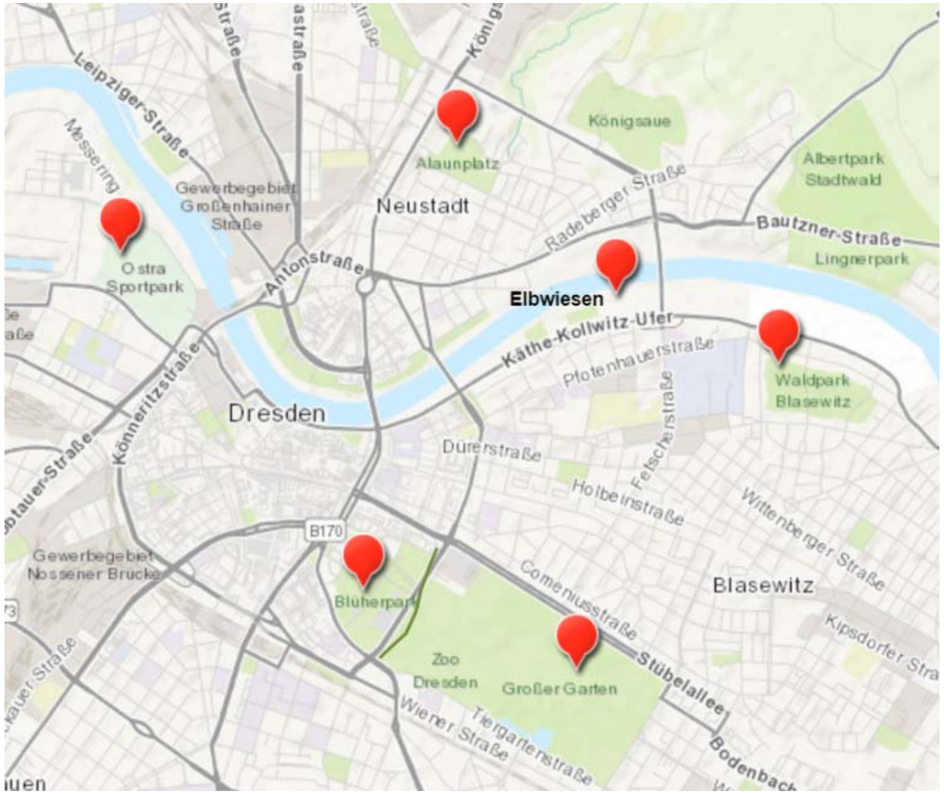
Use Case Scenarios

1. Landscape Development and Open Space Planning

Characterisation of the parks in Dresden: Großer Garten, Sportpark Ostra, Waldpark Blasewitz, Blüher Park, Alaunpark and the open space in Elbwiesen.

2. Characterisation of a Neighbourhood

Characterisation of a neighbourhood: The neighbourhood 'Wilsdruffer Vorstadt' in Dresden was analysed as it was analysed by some projects and targeted for discussions.



Großer Garten, Sportpark Ostra, Waldpark Blasewitz, Blüher Park, Alaunpark and Elbwiesen

Use Case Scenarios
Landscape Development and Open Space Planning

What are the typical activities in parks?
Which parks are trendier in the city?

280 points were observed on Sportpark Ostra (image no. 2). After, Großer Garten seemed to be popular. Fewer points were shown on Blüher Park on the west side of Großer Garten (image no. 1)

Observed Activities in Großer Garten and Sportpark Ostra : Riding bicycle, football, running, volleyball and basketball. American Football was a distinct activity observed on Sportpark Ostra, differently from other parks.

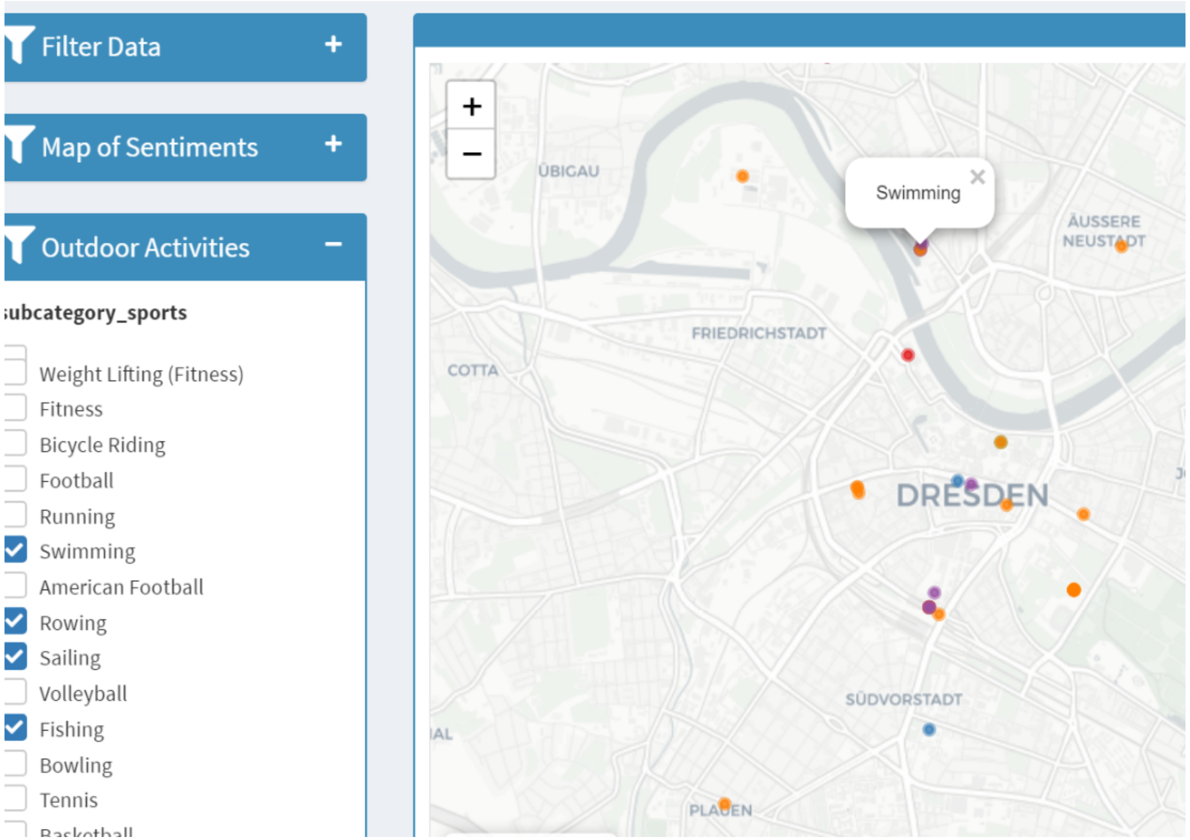
In Alaunpark, only a few points were classified in this subcategory (image no. 3). The number of points increased when “Eat & Drink” and “Mental Activities & Relaxation” were applied.

25 cluster points were on Waldpark Blasewitz, and these activities were tennis, running and general fitness (image no 4). No clustering could be observed on Blüher Park (image no. 1).

The most common activity was detected as bicycle riding and running at Elbwiesen. Unlike other parks, swimming, surfing, fishing and rowing activities were noticed.

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)

- **Distinct activities that were observed around the river Elbe**: Swimming, fishing, surfing and rowing performed. After investigation of the use of this area, possible development or landscape implementation of Elbwiesen can be evaluated.
- **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.
- **The use of Blüher Park:** It is important to analyse to understand why any posts were not assigned there, in “Outdoor Activities & Sports” subcategory.



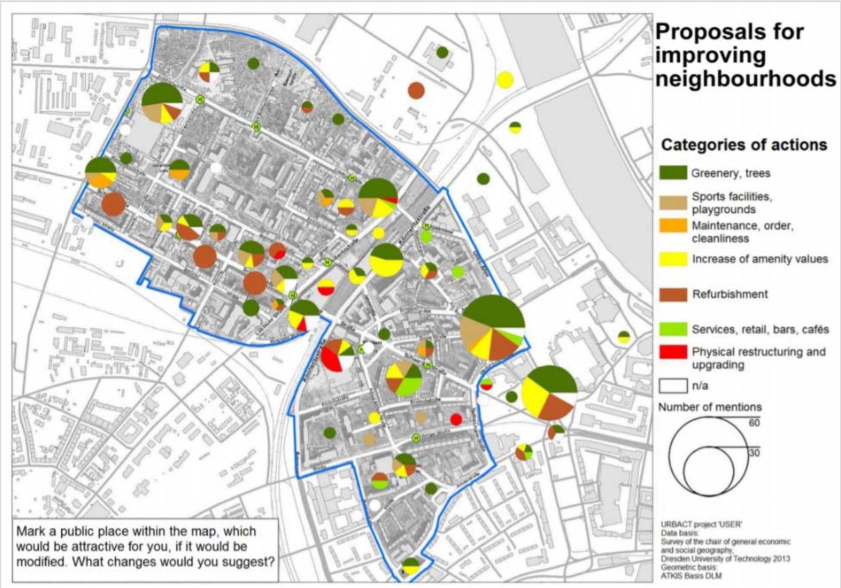
Swimming, rowing, sailing, fishing activity spots

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

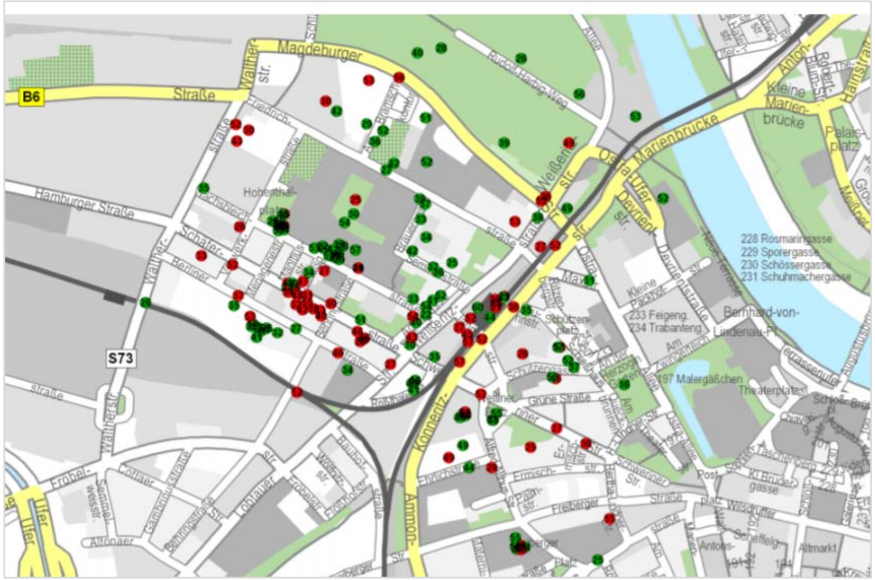
Is there a significant change in the type of activities or frequency of visits by time?

- The detection of temporal changes in activities was done by using the heatmap.
- Growth over time could be clearly observed.
- Is this because of the increasing popularity of social media or it indicates a growth of using the parks?

Use Case Scenarios
Characterisation of a Neighbourhood



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



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

USER was a project focusing on public spaces and conducted between 2013 and 2015 by URBACT programme, which promoted sustainable urban development (URBACT, 2015).

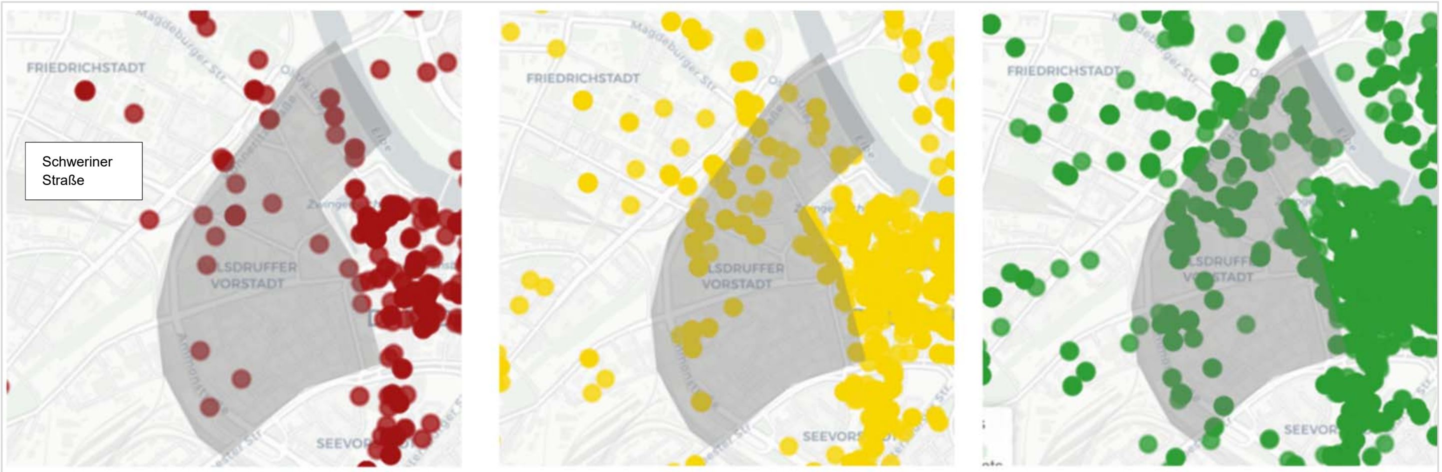
The project USER had chosen Wilsdruffer Vorstadt as their pilot site, and surveys were conducted for effective planning decisions and to ensure public participation.

Use Case Scenarios
Characterisation of a Neighbourhood

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

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

Findings from Wilsdruffer Vorstadt area



Geovisualisations of "Negative"(left), "Neutral"(middle) and "Positive"(right) sentiments

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

Posts' locations categorised as "Negative", "Neutral" and "Positive"

Use Case Scenarios (Characterisation of a Neighbourhood) *Summary*

- Landmarks could be easily identified in the neighbourhood.
- 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.
- 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.

- 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.
- Interactive map and filtering features helped characterise specific areas and give an idea about the use of the city.
- 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.

Use Case Scenarios (Characterisation of a Neighbourhood)
Shortcomings

- Filtering the “Recreational and Open Space” subcategory failed to evaluate parks, as negative – neutral – positive sentiments were compacted in the same places. No successful comparison could be made with the findings of USER project.
- Inconsistency of categories and places were found. For example, 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.
- <u>The map did not provide absolute accuracy and specific information about the opinions and needs of people.</u>

The Discussion

Contributions to Current Research

Previous investigations used LBSM data in urban studies to discover urban dynamics. 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 but the use of emojis was not explored to detect activity and spatial patterns.

- A taxonomy of emojis for urban studies was generated.
- A new attempt was made to draw the symbols of emojis as a word cloud.
- An interactive geovisualisation method was adopted for the interpretation of emojis usage in LBSM.

The Discussion

Limitations

Emojis are interpreted differently between people (Hauthal, Burghardt and Dunkel, 2019) and <u>some factors like age or gender</u> affect emoji usage (Lu et al., 2016). <u>Credibility and trustworthiness</u> are still controversial topics using social media information (Moturu and Liu, 2011).

- The use of emojis differs among users; the context of post and choice of emoji do not have to match to each other.
- 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.
- Locations did not always point places but larger regions. For example, in our data, approximately 14% of posts were geolocated in “Dresden, Germany”.
- Users tend to look positive in social media. 75% of posts were assigned as positive. Does that indicate the degree of satisfaction from the places?
- 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.

The Discussion

Future Work

- An improved methodology and approach to overcome the problem of assigning one post into multiple categories because of the containing emojis
- A new visualisation method where the size of clustering point represent the numbers of clusters
- A need for a finer investigation of emoji usage and their relation to places and activities
- An empirical study to be performed regarding both emotions, emojis and spatial areas to evaluate the results and to improve the methodology and categories
- Stronger privacy protections to prevent possible harms

Conclusion

- This study strengthened the position that LBSM is a useful resource for the urban planning profession.
- The use of emoji taxonomy and the geovisualisation have been shown to be advantageous to use as an information source.
- Emoji usage in social media can aid to assess subjective values, analyse different activity types patterns, landmarks, temporal changes and sentiments in the city.
- However, considering the limitations of using LBSM, proper care should be taken when taking emoji usage in social media as a source of information.

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