Towards a GeoSocial landmark identification model

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Towards a GeoSocial Landmark Identification Model

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Summary: *Research in human wayfinding shows, that integrating landmarks in route descriptions increases the success rate of navigational tasks for pedestrians. The salience of such landmarks is commonly measured using so called landmark dimensions. However, data collection for their attributes is difficult and time-consuming. A new promising data source emerged with the rise of geolocated social media content. We present a model to identify landmarks based on a social dimension using this content. We calculate a GeoSocial Score of objects in Augsburg using measures harvested from geosocial data and compare the outcomes with results of a survey. We conclude that geosocial data represent a reliable source of information to identify landmarks for pedestrians.*

Introduction

Landmarks are important elements for the communication of route descriptions, the orientation in, and navigation through space (Lynch, 1960; Allen, 2000; Michon and Denis, 2001). Most authors dealing with landmark identification build on the definitions of Sorrows & Hirtle (1999) and Raubal & Winter (2002) for landmark dimensions. These are the visual, the semantic, and the structural dimension. Other approaches focus on perceptual, cognitive, and contextual dimensions to model landmark salience (Caduff & Timpf, 2008). However, all of these approaches have in common that they need a wealth of different data sources to collect the information for all the attributes of these dimensions (Nuhn & Timpf, 2017). Due to the lack of data density, landmarks have hardly been picked up in actual, running navigation systems for pedestrians (Richter, 2017). The only service so far offering landmark-based verbal instructions is Whereis (Duckham et al., 2010). The underlying approach uses categories, which requires only data of an object's type and geographic location to determine an object's suitability as a landmark. However, this approach is based on the exploitation of points of interest (POIs) while landmarks are not limited to POIs (Richter & Winter, 2014).

These drawbacks can be overcome by using the social dimension, which describes "the way an object is practiced and recognised by a person or a group of people" (Quesnot & Roche, 2014 (p.1)). Since we are living in a 'geo-data-rich society' (Boulos, 2005), geospatial information to feed the social dimension is more accessible than ever. Volunteered Geographic Information that is produced by a large number of private citizens (Goodchild, 2007) includes data collected in social web platforms, such as Google place types (Google Place Types, 2022) and Foursquare (Foursquare, 2022). Quesnot & Roche (2014) argue that geosocial data represent a reliable source of information to precisely measure landmark semantic salience in an urban area. Their approach is based on Social Location Sharing, which consists of a check-in, which claims "I am/was at that place". Quesnot & Roche (2014) do not include Google Places API because it does not provide the information about check-ins. However, the Google place type, which describes an objects function, is a valuable source to identify social landmarks. We base our calculations on the user-generated Google place database, which is regularly updated by internet users (Quesnot & Roche, 2014). Furthermore, we consider Foursquare data, since they are a valuable source for the extraction of attributes regarding social prominence. We develop a GeoSocial model considering a social dimension and argue, that the model fed with data from Google place types and Foursquare is capable to identify landmarks, which would also be selected by humans. We apply the model in a pedestrian navigation scenario, where landmarks should be identified to be included in route directions. Finally, we evaluate the model by comparing the outcomes to the results of a survey.

GeoSocial Model – Basics

Our model considers the attributes place type, uniqueness, social prominence, and social activity to quantify the social dimension. We assign salience values to each place, based on these attributes and calculate a GeoSocial Score (GSS) to quantify the social salience of an object at a decision point (DP).

Place Type

We extract place types from Google Places database within a 50 meter radius around a DP. We assign all these places a salience value, based on the object's category of place type. Rousell and Zipf (2017) derive OSM place types, which are stored in each features attribute table, and reclassify them into broader, more general place type categories. They assign a weight value to each category, based on previous work of Duckham et al. (2010). We adapt their categorisation and transfer it to Google place types (Tab. 1). We introduce the weight values as tweight in our model.

Tab. 1: Place type category weight system.

Category	tweight	Google Place Types
shopping	0.8	clothing store, drugstore, jewelry store
grocery	0.8	supermarket, grocery store
gastronomy	0.7	café, bar, restaurant, bakery
health	0.5	doctor, dentist, pharmacy
office	0.5	insurance agency, lawyer, government office
service	0.5	hair care, travel agency, bank
transportation	1.0	rail station, transit station
religion	1.0	church, place of worship
leisure	1.0	park, plaza, sport facilities
tourist attraction	1.0	fountain, monument, theater

Uniqueness

Uniqueness investigates places and objects, where their associated function stands out in contrast to nearby objects (Quesnot and Roche, 2014). Following Rousell and Zipf (2017) and Quesnot and Roche (2014), we calculate the uniqueness score of an object as the ratio between the amount of places with the same place type (LM_{type}) and the total amount of objects in a 50 m radius at a single DP (LM_{total}). The result of this is subtracted from 1. In order to utilise the uniqueness metric in the GeoSocial Score as a weight multiplier, we apply a normalisation function to re-scale all values into a new range of 0.7 - 1.0. We choose the lower bound of uniqueness higher than 0 because of the multiplication of factors. We set the lower bound to 0.7 to avoid an overly low GSS which would result in case we would, e.g., use a lower bound of 0.001. Highly unique candidates get a unique value close to 1, while less unique places are close to a value of 0.7 (Eq. 1).

$$\text{unique} = 1 - (LM_{type}/LM_{total}) \rightarrow \text{norm}_{0.7\text{-}1.0}. \qquad (1)$$

Social Prominence

Bernardini and Peeples (2015) describe prominence as the 'Viewership' of elements in the landscape, in other words, the total number of viewers. In case an environmental feature has a great viewership, it is referenced a lot of times and thus perceived as salient. Each registered Google place can be reviewed by rating the place and leaving a written review. We apply a normalisation method per set of objects at a DP. The most reviewed place at a DP gets a weight value of 1.0, while the lowest rated place gets a weight value of 0.5 (Eq.

2). This means that the normalisation range for social prominence is with 0.5 higher than the range for uniqueness, since we consider social prominence as more important in this work.

$$\text{prominence} = LM_{review} \rightarrow norm_{0.5\text{-}1.0}. \qquad (2)$$

Social Activity

The two indicators derived from Foursquare are the amount of likes and the number of uploaded photos of a place. These indicators reflect the social activity of objects (Eq. 3). At each DP the range of objects' social activity score is re-scaled into a range of 1.0 for the lowest values and 1.3 for the highest values. This is due to the fact, that some places do not have any Foursquare data, namely no measurable social activity. This way, they remain unchanged when multiplied by a 1.0 weight but are normalised to the same range size (0.3) as uniqueness.

$$\text{activity} = LM_{likes} + LM_{photos} \rightarrow norm_{1.0\text{-}1.3}. \qquad (3)$$

GSS

We multiply the weights for the place type, the uniqueness, as well as the social prominence and activity to obtain the GSS (Eq. 4) for each object at a DP.

$$GSS = tweight * uniq * prominence * activity \qquad (4)$$

Eq. 5 shows the calculation steps for a 'Starbucks' café. We apply a tweight = 0.7 for the place type category gastronomy (Tab. 1). There are 5 other objects at the DP, making the café the least unique place type (uniqueness = 0.7). The 'Starbucks' café has 510 reviews (prominence = 0.61) and 23 likes and fotos (activity = 1.018). The resulting GSS is 0.30.

$$GSS_{Starbucks} = 0.7 * 0.7 * 0.61 * 1.02 = 0.30 \qquad (5)$$

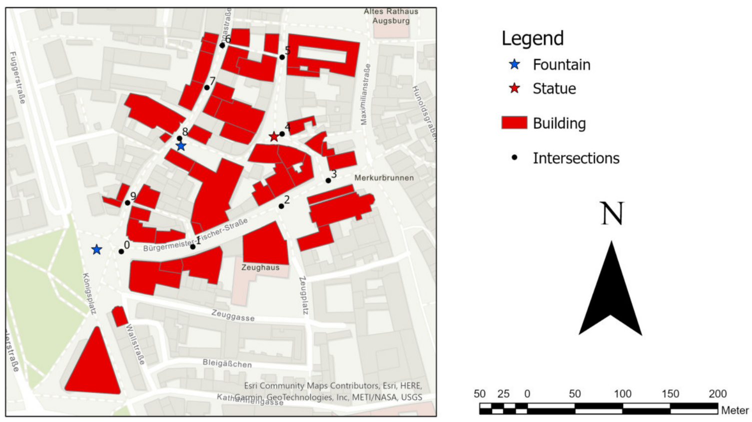

Fig. 1: Investigation area.

GeoSocial Model – Application

In this chapter we demonstrate the GeoSocial Model. We use a part of the inner-city of Augsburg as investigation area (Fig. 1). We harvested the data for this study between September and October 2021 from Google Places and Foursquare.

Place Type and Uniqueness

We identify 116 places in the investigation area. The place type and the resulting place type uniqueness are the first parameters in the GSS. With a total amount of 473 tags, each object has 4 tags on average. We classify the place types into the place type categories (Tab. 1). Fig. 2 shows the overall distribution of place type categories. The high number of shopping (47) and gastronomy (25) places is typical for pedestrian downtown areas.

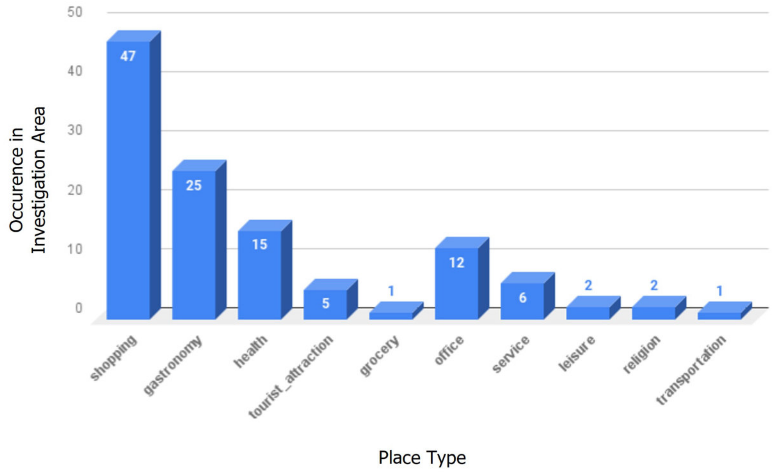

Fig. 2: Place type category in the investigation area.

Social Prominence

In order to eliminate noise that derives from Google Places, all places in the investigation area with less than 10 reviews are not used for further analysis. In total, 16904 reviews were extracted. Tab. 2 shows the most reviewed places on Google by place type category, highlighting the best place per place type. The 'McDonalds' is the most prominent place in the investigation area followed by the 'Starbucks' and 'Dunkin' Donuts'. All three of them are listed in the leading quick service restaurant companies of Germany by 2019, with the same hierarchical relationship (Statista, 2019). This may indicate that the social prominence of gastronomy places is linked to the quantitative popularity in Germany.

Tab. 2: Social prominence - most reviewed places by type.

Name	**Category**	**Reviews**
McDonald's Restaurant	Gastronomy	2376
Thalia	Shopping	1577
Travel agency	Service	523
REWE	Grocery	479
St. Anne's Church	Religion	295
Weberhaus	Tourist Attraction	204
Königsplatz Parc	Leisure	187
OZA	Health	142
Stadtwerke Customer Centre	Office	108
Moritzplatz	Transportation	22

The three most reviewed shopping places are the ’Thalia’ bookstore (1577 reviews), ’SCHMID’ (1128) clothing store, and the ’o2 Shop’ (898). All of these mentioned places are chains that are present in several cities. This may also indicate that the quantitative popularity in Germany is linked to the local social prominence in the investigation area. More regional and local points-of-interest like St. Anne’s Church (295), Weberhaus (204), or Moritzplatz (22) tend to have lower social prominence values.

Social Activity

Out of 116 places in the investigation area, 31 places show Social Activity derived from Foursquare database. In other words: only 26.72% of Google Places have associated Foursquare activity data. All places with type tourist_attraction in the investigation area show social activity. These places have on average 4.8 uploaded photos. Most photos are uploaded for the Fuggerdenkmal (Fig. 5). The other place types show similar patterns, with gastronomy and shopping covering 67.7% of all social activities.

GSS

Fig. 3 shows a scatter plot of the GSS for all 116 places. It is visible that most shopping places show low scores, with a few exceptions. These exceptions are prominent and draw great social significance. Gastronomy places scatter the most with diverse GSSs across the whole scale. Health, office, and service places reveal to be not socially active. The remaining place types tend to achieve higher scores of the GSS (tourist_attraction, grocery, leisure, and religion).

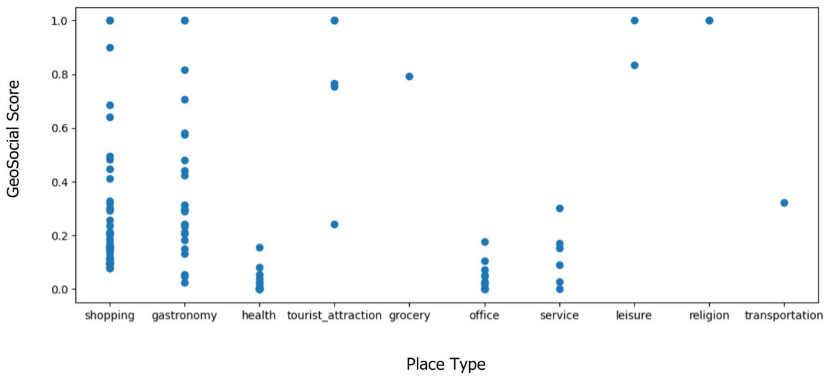

Fig. 3: GSS by place type.

GeoSocial Model – Evaluation

We compare the results of the GeoSocial model to the results of a survey. 51 participants selected at DPs in the inner-city (Fig. 1) objects useable as a landmark (Nuhn, 2020). We assign the number how often it was selected as a landmark to each object in the investigation area and compare this metric to the normalised GSS (highest GeoSocial Score at DP is 100%, the lowest is 0%). Then, we calculate a Pearson Correlation Coefficient. The coefficient indicates a moderate correlation (0.613) (Asuero et al., 2006). This suggests, that the GSS outputs similar objects as landmarks as the survey participants choose, but some adaptations might be needed in future work (see Conclusion and Outlook). Tab. 3 – Tab. 5 show the results of the comparison for 3 selected DPs (Fig. 4 – Fig. 6).

- DP 3: The model and the survey participants identify both the cultural building ’Weberhaus’ as most prominent landmark (Tab. 3, Fig. 4). There is one building, which hosts multiple places belonging to shopping, gastronomy, and transportation (Fig. 4, Moritzplatz). We select the place with the highest score as a representative for that building polygon since most people associate one specific function with a building and often may not recognise multiple functions of a building.
- DP 4: The tourist attraction Fuggerdenkmal achieved the highest GSS and is selected the most from the survey participants (Tab. 4, Fig. 5). One building has no Google place type

although it hosts a museum. We extracted place types within a 50 meter radius around a DP. However, the Google place of the museum is not located within the radius. This is because the place types are located at the centroid of the polygons. Thus, in this case, the GSS cannot be calculated.

- DP 8: St. Anne's Church reaches the highest GSSs (Tab. 5, Fig. 6). It is not accessible from the DP and, additionally, is located behind a wall (Fig. 6). We assume that reviews, likes, and photos have been taken from people who entered the church from a DP on the other site of the church. The survey participants did not select St. Anne's Church but "Dr Scherer" as the most outstanding landmark. We believe that the participants did not select this landmark because of its health category but because of its function as a bank (Kreissparkasse) which is recognisable by an explicit mark. One building is missing in both, Google Places and Foursquare, since it was neither reviewed nor liked. Thus, the GSS cannot be calculated.

Based on these findings we can confirm that the model fed with data from Google place types and Foursquare is capable to identify landmarks, which would also be selected by humans. However, there might be adjustments necessary to improve the Geoscoial Score, which are discussed in the next Section.

Fig. 4: DP 3.

Tab. 3: GSS DP 3.

Name	Category	Prominence	Activity	GSS	Landmark Selection
Weberhaus	Tourist Attraction	204	9	1	42
Kutscher + Gehr	Shopping	129	0	0.33	0
Moritzplatz	Transportation	22	0	0.32	5
cheapenergy24	Service	132	0	0.17	3
Dr. Anstett	Health	38	0	0.03	1

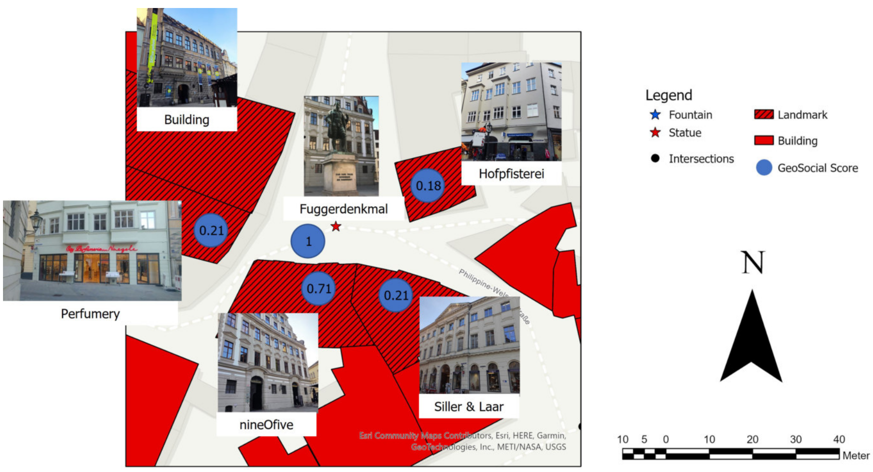

Fig. 5: DP 4.

Tab. 4: GSS DP 4.

Name	Category	Prominence	Activity	GSS	Landmark Selection
Fuggerdenkmal	Tourist Attraction	143	14	1	39
nineOfive	Gastronomy	270	3	0.71	6
Siller&Laar	Shopping	70	3	0.21	0
Perfumery	Shopping	71	2	0.21	0
Hofpfisterei	Gastronomy	17	0	0.18	0
Building (Museum)	-	-	-	-	6

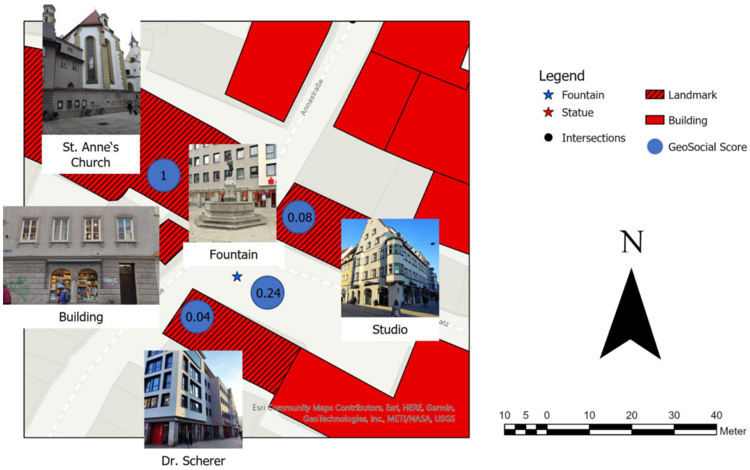

Fig. 6: DP 8.

Tab. 5: GSS DP 8.

Name	Category	Prominence	Activity	GSS	Landmark Selection
St. Anne's Church	Religion	295	23	1	9
Fountain	Tourist Attraction	14	1	0.24	15
Studio	Shopping	43	0	0.08	1
Dr. Scherer	Health	48	0	0.04	23
Building	-	-	-	-	3

Conclusion and Outlook

The Geosocial data, Google and Foursquare, represent a reliable source of information to identify landmarks for pedestrians. However, several problems still need to be addressed in future work. Our attributes are scaled only locally, that is there is always an object with the maximum GSS for each DP, independent of the absolute numbers of, e.g., views, likes, or photos. Thus, an alternative might be a global GSS for all the decision points. However, then, we need to find a solution for DPs where no landmark is identified. Additionally, recency of likes and reviews could be considered in future adaptations of the GSS. For example, a place with more current ratings could be more prominent than one with older ratings. Furthermore, we noticed that sometimes no reviews, likes, or photos are available for a specific object (compare DP 8). Moreover, sometimes not the landmark with the highest GSS, but another landmark seems more important to humans (compare DP 8). Additionally, landmarks with a high GSS might be located at a street intersection but not identified as most important for participants, since they are not accessible from the DP (compare DP 8). Furthermore, the location of the place type might not fall in a 50 meter radius around a DP (compare DP 4), although it could be an important landmark at the DP. The landmark dimensions can consider attributes such as accessibility in the structural dimension and the availability of explicit marks in the semantic dimension. Thus, the combination of our social dimension with the conventional landmark dimensions, seems promising for future work.

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