ISPRS Int. J. Geo-Inf. **2015**, *4*, 1-31; doi:10.3390/ijgi4010001

OPEN ACCESS

ISPRS International Journal of
Geo-Information
ISSN 2220-9964
www.mdpi.com/journal/ijgi/

Article

Measure of Landmark Semantic Salience through Geosocial Data Streams

Teriitutea Quesnot * and Stéphane Roche

Center for Research in Geomatics, Université Laval, 1055 Avenue du Séminaire, Pavillon Louis-Jacques Casault, Québec (QC) G1V 0A6, Canada;
E-Mail: stephane.roche@scg.ulaval.ca

* Author to whom correspondence should be addressed; E-Mail: teriitutea.quesnot.1@ulaval.ca; Tel.: +1-418-264-4570.

Academic Editors: Alexander Zipf and Wolfgang Kainz

Received: 19 July 2014 / Accepted: 17 December 2014 / Published: 30 December 2014

Abstract: Research in the area of spatial cognition demonstrated that references to landmarks are essential in the communication and the interpretation of *wayfinding* instructions for human being. In order to detect landmarks, a model for the assessment of their salience has been previously developed by Raubal and Winter. According to their model, landmark salience is divided into three categories: *visual*, *structural*, and *semantic*. Several solutions have been proposed to automatically detect landmarks on the basis of these categories. Due to a lack of relevant data, semantic salience has been frequently reduced to objects' historical and cultural significance. Social dimension (*i.e.*, the way an object is practiced and recognized by a person or a group of people) is systematically excluded from the measure of landmark semantic salience even though it represents an important component. Since the advent of mobile Internet and smartphones, the production of geolocated content from social web platforms—also described as *geosocial* data—became commonplace. Actually, these data allow us to have a better understanding of the local geographic knowledge. Therefore, we argue that geosocial data, especially *Social Location Sharing* datasets, represent a reliable source of information to precisely measure landmark semantic salience in urban area.

Keywords: automatic landmarks detection systems; landmarks; landmark semantic salience; localness; online social networks; social location sharing; wayfinding

1. Introduction

Researchers of MIT's Senseable City Lab who worked on *Real-Time Cities* brought the potential of location-based datasets into focus in the understanding of urban dynamics [1–6]. Since the rise of mobile Internet and smartphones, people became *sensitive sensors* able to quickly relay and produce geographic information [7]. Citizens are now considered as *passive* sensors as well as *active* sensors [8]. In the first case, data are transmitted in a more or less constant flow (e.g., when users of smartphones leave the geolocation functionality activated) while in the second one, users are producing spatial information deliberately (e.g., a Swarm check-in or a geolocated Facebook publication). A large part of this "*Volunteered Geographic Information*" (VGI) [7] is produced from social web platforms, such as Facebook, Twitter and Swarm (previously Foursquare). Since the geolocation functionality is now available on each of these platforms, users are able to geo-tag their posts (*i.e.*, comments, photos, videos or tweets). Among the "*Big Geosocial Data*" avalanche [9], *Social Location Sharing* [10] and especially *check-in* datasets enable us to observe and measure concretely the way that citizens daily interact with urban places. Indeed, researchers in digital footprints claim that social dimension of places are captured within these spatial data [11]. Since the local geographic knowledge (*i.e.*, localness) is now accessible, we should take this opportunity to improve relationships between citizens and their cities.

Actually, the analysis of such data in this context matches with the concept of *smart city*. Indeed, the latter represents for now the appropriate solution facing the steady increase of global urbanization. According to Giffinger *et al.*, a smart city is usually divided into six categories: the smart *economy*, the smart *environment*, the smart *governance*, the smart *living*, the smart *people* and finally the smart *mobility* [12]. The joint improvement of these six interrelated categories depends on the effective management and exploitation of Information and Communication Technologies (ICT) and digital data [13]. Nevertheless, a smart city cannot exist without any *human capital* [14]. More precisely, citizens should be firstly "*spatially literate*" in order to contribute to the enhancement of the next generation of *spatially enabled* cities [15].

Thus, we are asking the following global research question as a starting point: *can we improve the urban intelligence using geosocial data generated by users of online social networks*? We argue that geolocated content published on Facebook and Swarm can be exploited to enhance citizens' spatial literacy. More precisely, check-ins datasets can be used to improve human *wayfinding* and *smart mobility* by detecting relevant semantic landmarks. Lots of research in *wayfinding* is done in order to enable individuals to reach as quickly as possible a desired destination, to help people with disabilities by designing cognitively appropriate orientation signs, and reduce the fact of being lost [16]. Therefore, designing tools that effectively support people's wayfinding remains a major concern.

In order to defend our argument, we detail in the following section a brief state of art related to the concept of *wayfinding*. Then, we focus both on *landmarks* and systems designed for their automatic detection. The fourth section puts forward the reasons why check-ins are, in our opinion, a reliable source of information to identify semantic landmarks. More precisely, three scores based on Facebook and Swarm check-ins are suggested in order to measure landmark semantic salience. Finally, the last section of this article presents concrete examples where these scores are applied with real check-ins datasets harvested from Facebook and Foursquare APIs.

2. Human Wayfinding

Being able to find one's way is a concern for humans since the dawn of time but the term "wayfinding" appeared in the literature only since the mid-20th century.

2.1. Definition of Human Wayfinding

The formal definition of the term "*wayfinding*" is generally attributed to Lynch who used this expression in his work on the "*imageability*" of the city. He defines wayfinding as "*a consistent use and organization of definite sensory cues from the external environment*" [17] (p. 3). According to him, wayfinding consists in scanning the physical environment in order to create its mental representation. More precisely, we store and organize distinctive objects in our brain to create a coherent image. Lynch ranks these objects into five categories: (1) *landmarks*, which are external cues that can be seen from afar; (2) *nodes*, which are strategic points; (3) *paths* which, unlike (4) *edges*, correspond to the elements on which individuals move; and finally (5) *districts*.

Downs and Stea have proposed a theoretical framework that identifies the main key factors of the wayfinding success [18]. They distinguish four processes [16]:

- *Orientation* (*i.e.*, being aware of our relative position compared to the final destination);
- *Route selection* (*i.e.*, establishing a route in order to reach the final destination);
- *Route control* (*i.e.*, following the route previously established);
- *Recognition of destination* (*i.e.*, realizing that we have reached the final destination).

It is now commonly accepted that wayfinding corresponds to the process of identifying and following a route in order to reach a desired destination [19]. Montello and Raubal consider it as a part of the navigation that corresponds to a spatial-cognitive task that "*includes specific tasks, such as creating and choosing routes, establishing and maintaining orientation with respect to one's starting location or with respect to external features or places, recognizing how landmarks spatially relate to other landmarks or other aspects of the environment, judging distances, remembering sequences of turns, and remembering the locations of objects and events*" [20] (p. 251). According to this definition, *wayfinding* and *locomotion* are both separated components involved together in the process of *navigation*. To sum up, wayfinding process largely depends on our sense of orientation and environmental cues, such as punctual and linear items (e.g., buildings and roads) as well as areas (e.g., neighborhoods). These objects constitute a *spatial knowledge* that (1) is stored in our memory, particularly when we evolve in an unfamiliar environment; and that (2) we are able to recall when necessary (e.g., find our way or help someone to do so by providing wayfinding instructions).

2.2. Human Spatial Knowledge

The acquisition of spatial knowledge is done through *spatial abilities* commonly grouped under three categories [21]: (1) *spatial relations*, *i.e.* understanding the fundamental spatial relationships; (2) *spatial visualization*, *i.e.* viewing and storing these relationships; and (3) *spatial orientation*, *i.e.*, orienting oneself in space. On the one hand, this acquisition can be done *via* a direct experience of space (*i.e.*, primary learning), and on the other hand, through supports, such as maps [22].

Moreover, three theories associated with the primary learning cohabited. The first one considers landmarks as the basis of spatial knowledge (routes are secondary information attached to them). The second theory claims the contrary; *i.e.*, lines are the main component. The last theory suggests that the acquisition of spatial knowledge is organized as a series of vistas stored in our memory [22].

That being so, Siegel and White's theory [23] was the most influential in the area of cognitive mapping. Better known under the acronym LRS for *Landmark-Route-Survey*, this theory suggests that our cognitive map is hierarchically organized into three levels: (1) *landmark knowledge*, (2) *route knowledge*, and finally (3) *survey knowledge* (*cf.* Figure 1). Their theory is sequential because it is largely inspired from the work of Piaget on topological, projective and Euclidean dimensions of space.

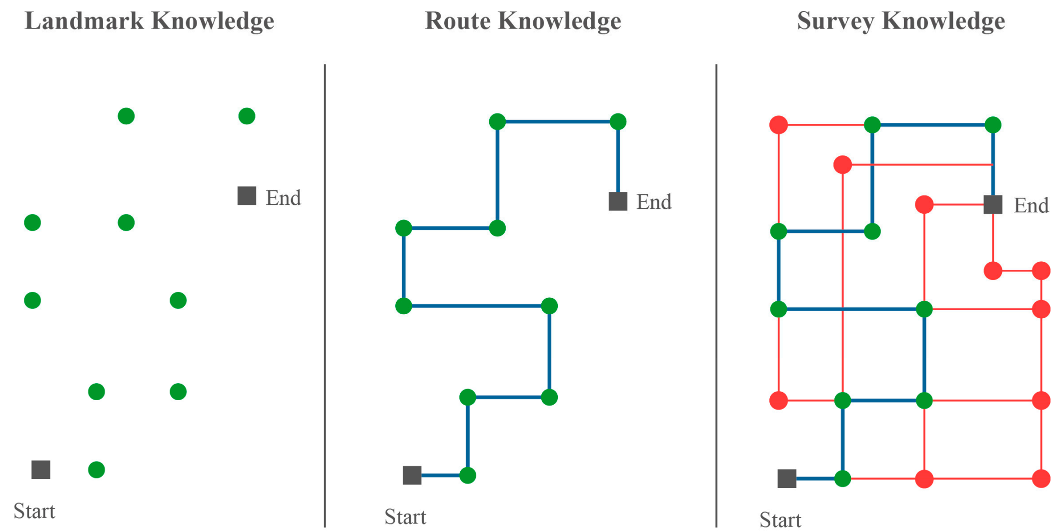

Figure 1. Landmark-Route-Survey Knowledge theory according to Siegel and White [23].

According to this theory, landmarks form the base of spatial knowledge. Unlike Lynch's restrictive definition [17], it is now widely accepted that almost every item can be considered as a landmark: buildings, trees or even parked cars (*cf.* [24,25] for concrete examples of landmarks). Route knowledge is a sequence of paths where nodes correspond to the main landmarks previously memorized. The final step is the acquisition of survey knowledge; which is usually represented by a classic bird's-eye view map. At this stage, we should be aware of the environment's overall configuration and the potential relationships between its different spatial components. Plus, we are supposed to be able to estimate distances, directions and take shortcuts to reach a destination as quickly as possible. Although researchers have proposed some alternative theoretical frameworks (e.g., [26]), Siegel and White's theory is still relevant. Only its sequential nature is called into question because it has been demonstrated that both adults and children were able to memorize a route without necessarily having landmarks in mind (see Chapter 5 of Kitchin and Blades [22] for a discussion).

2.3. Assisted Wayfinding

Three media support wayfinding: written materials, maps, and route instructions [22]. Traditional maps were the main orientation support until the arrival of location-based services. Mapping applications, such as Google Maps, Yahoo Maps or Apple Plan, are now commonly used as a personal navigation aid tool. Like the firsts GPS car navigation systems, these mobile applications offer two routing algorithms: the *shortest* and the *fastest* route. However, wayfinding instructions (*i.e.*, verbal directions) provided are not cognitively adequate since they are exclusively based on streets names. Indeed, some researchers have focused their work on the structure of instructions given by individuals in a wayfinding context and found that they were essentially composed of landmarks (*cf.* [27,28] for an overview). For example, in the experimentation of Daniel and Denis [29], every route instructions contained landmarks located at *decision points*. We distinguish four types of decision points: (1) the *choice points*, located at the intersections where the traveler have to perform an action (*i.e.*, turn left or right); (2) the *potential choice points*, also located at intersections, but in this case the traveler do not have any action to perform; (3) the *on-route points*, located along the traveler's path; unlike (4) *off-route points*, which are used to provide global orientation information [30].

This trend was confirmed in a subsequent study (*cf.* [31]) and supports Denis' concept of "skeletal description"; *i.e.*, a set of condensed route instructions that only contains the core landmarks and actions to execute [32]. Furthermore, Michon and Denis [33] as well as Tom and Denis [34] noticed that the references to street names in route instructions implied significant delay in travel time compared to landmark-based instructions. Travels based on street-names instructions appeared jerky, involving frequent breaks to ensure the *route control*. Moreover, the memorization of a route is greatly facilitated when the instructions are composed of landmarks combined with an action to perform [35]. In other words, the combination of landmarks with an action to realize remains more important than the amount of landmarks present in the instructions [36].

To conclude, maps based on route knowledge (*i.e.*, a map that emphasizes landmarks and paths) are more cognitively adequate than survey knowledge-based maps [27,32,37]. In our opinion, it is not a coincidence if the latest version of Google Maps offers now a personalized map that highlights places of interest for each user. However, there is not any mapping platform that offers verbal directions based on landmarks.

3. Toward the Automatic Detection of Landmarks

On the basis of the findings briefly summarized above, some researchers focalized their works on various methods in order to evaluate landmark saliencies. The development of systems able to automatically detect relevant landmarks remains a major challenge.

3.1. Landmarks Salience and Automatic Landmarks Detection Systems

3.1.1. Formal Model of Landmarkness

As explained, landmarks can be considered (1) as *markers* (*i.e.*, an environmental cue) used to find one's way; (2) as an *organizing concept* of human spatial knowledge; and (3) as an *essential component of route instructions*. Nevertheless, a lack in the characterization of landmarks persisted. Consequently, Sorrows and Hirtle have proposed three categories of landmarks [38]. Firstly, *visual landmarks* are the most visually identifiable and memorable objects compared to surrounding objects. Secondly, *cognitive landmarks* are objects that stand out by their *meaning*: it may be an object that has a historical or a cultural importance, that stands out from the rest by its function (e.g., a pub located inside a campus), or simply an object that is valuable for a person or a restricted group of people. Finally, *structural landmarks* are characterized by their strategic position (e.g., a major intersection).

According to this definition, Raubal and Winter have developed a model that measures the salience of landmarks, also described as *landmarkness* (*cf.* Figure 2) [39]. Their model focuses on the attractive qualities of buildings' facades. The first quality, *i.e.*, the *visual attraction*, is the combination of several sub-categories, such as *facade's area* and *shape* as well as its *color* and *visibility*. The second attraction, called *structural*, is based on the structural elements identified by Lynch [17]; *i.e.*, *nodes*, *edges*, and *districts*. The last quality, *i.e.*, the *semantic attraction*, refers directly to Sorrows and Hirtle's *cognitive landmarks*. However, the model takes only into account facade's historical and cultural importance and explicit marks. Nothegger *et al.* have tested this model on buildings located in the streets of Vienna [40]. The findings were conclusive as the participants' selections of landmarks mostly coincided with those identified through the model.

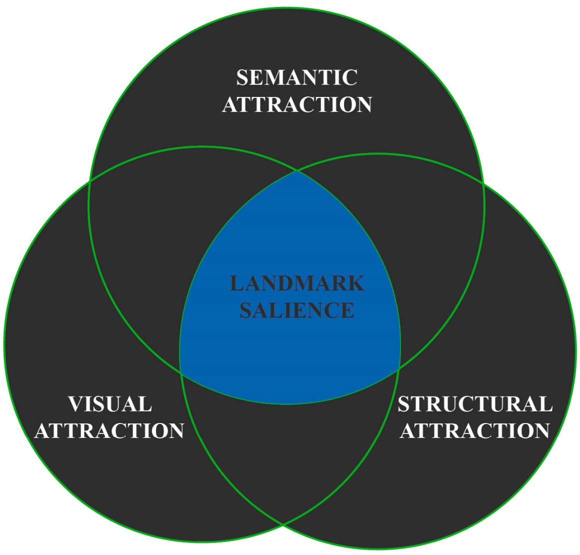

Figure 2. Landmark Salience according to the model of Raubal and Winter [39].

As a result, Raubal and Winter's model—which we will now refer as the original model—was considered as a significant advance in the field of landmark automatic detection. Therefore, it has been improved subsequently. Winter introduced the notion of *advance visibility* [41]. The idea is quite simple: the selection of a building as a landmark primarily depends on its advance visibility; *i.e.*, if it is visible from afar and very early in the process of navigation. In other words, hardly visible buildings will be *de facto* undervalued or even eliminated from the equation. Advance visibility is therefore a decisive parameter that should be combined with visual, semantic, and structural attractions. The second enhancement of the model is associated with Winter *et al.*'s notion of *focalization* [42]. They assume that the choice of a landmark is closely related to the context of navigation; more precisely: the *mode of traveling* (pedestrian or by car), the *type of traveling* (recreational or emergency), the *environment* and the *conditions of navigation* (urban or rural, day or night), and finally people's *spatial and cognitive abilities* (e.g., the degree of local knowledge of the environment). Consequently, Winter *et al.* propose to apply a weighting to each of the buildings' attractive qualities (*i.e.*, visual, semantic and structural) depending on the context of navigation. Thus, for example, the weighting of a nightclub's color attribute should be increased by night during weekends. Finally, Klippel and Winter enriched the notion of the *structural salience* [43]: the position of a building remains the decisive factor of its structural salience. In other words, if the building is easily recognizable (both visually and cognitively) thanks to its position, then it has a high structural salience.

3.1.2. Automatic Landmark Detection Systems

On the basis of the enriched original model, researchers have proposed several approaches to design automatic landmark detection systems (ALDSs) (*cf.* Table 1). More precisely, two generations of ALDSs clearly stood out. In both generations, landmark detection is based on the same global approach: (1) first of all, a neighborhood analysis is performed at each choice point; (2) among the buildings identified, various analysis of their attributes are performed in order to determine an outlier; and (3) this outlier is selected as the landmark candidate [44].

The first generation is generally related to Elias' research followed by Winter *et al.* [45,46]. Elias proposed a method that automatically extracts landmarks using a data mining approach based on Quilan's ID3 algorithm. Once a neighborhood analysis performed, the algorithm is applied sequentially to each building's attributes stored in a cadastral spatial database (e.g., building use, size of building, numbers of corners, orientation to the road, *etc.*). It produces a decision tree after each iteration: the shortest one represents the outlier and therefore the landmark candidate. Otherwise, Winter *et al.* developed an algorithm in order to establish a hierarchy of landmarks (*i.e.*, global and local landmarks) based on the heights of buildings [46]. Their method relies on the compute of polygons resulting from the Voronoi diagram and Delaunay triangulation. The ALDSs proposed by Elias and Winter *et al.* [45,46] are not suitable for a web deployment because on the one hand, it requires a heavy architecture—usually a geographic information system—and on the other hand, it consumes too much resources and time.

Table 1. Semantic salience criteria used for the design of automatic landmark detection systems (ALDSs).

References	Semantic Salience	Description
Raubal and Winter [39]	√	Historical and cultural significance of the building's facade; Explicit mark on the building's facade.
Elias [45]	√	Function of the building.
Winter [41]	Ø	Focus on buildings' visual salience (*advance visibility*).
Tomko [47]	√	Semantic Web.
Tekuza and Tanaka [48]	√	Semantic Web.
Klippel and Winter [43]	Ø	Focus on the buildings' structural salience.
Winter *et al.* [42]	Ø	Focus on the context of navigation (*mode of travelling*, *environment*, *etc.*).
Caduff and Timpf [49]	Ø	Focus on the buildings' visual salience (*distance*, *orientation,* and *visibility*).
Elias and Sester [50]	√	Brevity (*numbers of words used to refer the object*).
Richter and Klippel [51]	Ø	Focus on buildings' structural salience (*distance separating landmarks and decision points*, *relative positions of landmarks*).
Winter *et al.* [46]	Ø	Focus on buildings' visual salience (*height of buildings*).
Duckham *et al.* [52]	√	Ubiquity and familiarity of buildings; Length of description.
Schroder *et al.* [25]	√	Historical and cultural significance; Function.

The second generation of ALDSs relies on the web-based approach proposed by Duckham *et al.* [52]. The extended version of their algorithm (the Core LNM for Landmark Navigation Model) has been implemented in the Australian online route service *Whereis* for few years. Rather than focusing on individual attributes of each building, the algorithm takes into consideration buildings' top-level category. In their case study on *Whereis*, POIs are taken into account and their categories come from two different sources: the yellow pages service and a geospatial database of the Universal Publishers Pty Ltd. Once combined, these sources provide 170,000 POIs and 66 categories. Each category was evaluated by an expert group according to several criteria: *physical size*, *visual prominence*, *difference from surroundings*, *nighttime versus daytime salience*, *proximity to road*, *ubiquity and familiarity*, *length of description* (items that require short description are more suitable landmarks), *spatial extents* (point-based POIs are the best) and finally *permanence*. This assessment is done through a global suitability score. In order to identify a landmark candidate at each choice point, the extended algorithm of the Core LNM takes into account the *overall suitability* score of the object, its *uniqueness* and finally its *position compare to the road* (buildings located on the side of the road where the next turn is supposed to be performed are more appropriate). *Whereis* was the only platform that offered landmark-based verbal directions (*cf.* Figure 3). However, since its recent update, this functionality is no longer available.

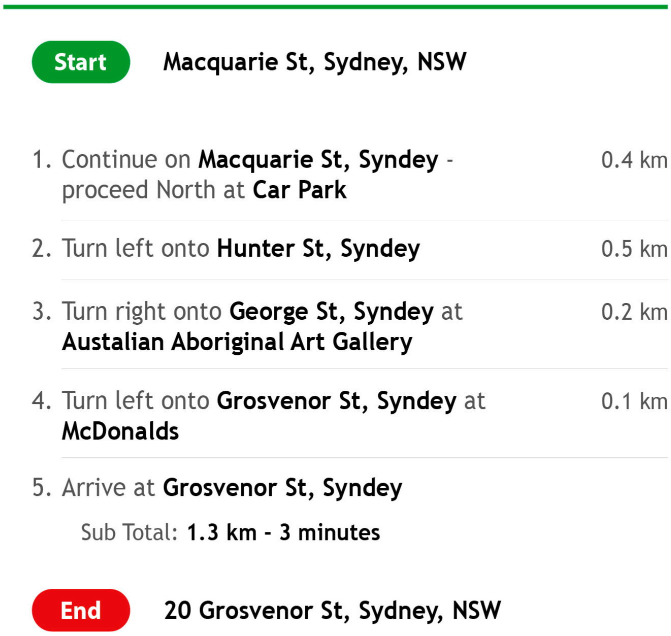

Figure 3. Example of landmark-based instructions given by the former version of the Australian route service *whereis*.

3.2. Challenges and Issues Related to ALDSs

Sadeghian and Kantardzic [44] identified downsides associated with the approaches proposed for the automatic detection of landmarks. Duckham *et al.*'s algorithm [52] is not directly concerned, since it was developed after the publication of their article. These main disadvantages are listed below:

1. First of all, ALDSs mostly focus on visual and structural attributes of buildings while their semantic meaning is also crucial (*cf.* Table 1). Moreover, traditional approaches are exclusively based on static and objective attributes (e.g., heights of buildings). Dynamic and subjective attributes, such as number of visitors, should also be taken in consideration. We did not identify any solution that takes into account such dynamic attributes.
2. Since the evaluation of actual weighting is difficult to evaluate, traditional approaches apply a uniform weighting to each objects' attributes. That being said, Winter *et al.* [42] give a trail to follow with their work on the context of navigation. Furthermore, Duckham *et al.* [52] apply adjustable weighting since their measure of landmarkness is route dependent.
3. Apart from few solutions (e.g., [53]), only buildings are taken into account. Other types of objects, like trees, are ignored. Yet, buildings are far from being the only item that can serve as landmarks for navigation [37]. Even if Duckham *et al.* acknowledge that objects other than buildings should be taken into account, their solution does not derogate from this rule [52].
4. Traditional solutions focus only on landmarks located at choice points or potential choice points. However, on-route and off-route points are also crucial in navigation [30]. We must state that the extended Core LNM includes the selection of landmarks off decision points.

Among all referenced approaches for the automatic detection of landmarks, Duckham *et al.*'s solution [52] appears to be the most promising: in addition to rectify most of the disadvantages indicated by Sadeghian and Kantardzic, their algorithm does not consume a lot of geospatial data. However, the use of subjective and dynamic attributes for the measure of semantic salience is not supported because of the lack of relevant data. That being said, as underlined by Hirtle [54] and Richter [55], the exploitation of user-generated content is currently the most suitable option to fill this gap.

3.3. The Potential of Crowdsourcing for the Automatic Detection of Landmarks

Measuring landmark semantic salience through dynamic data was almost inconceivable when Raubal and Winter's model was formalized. Thanks to the spatial information now daily delivered by citizens, this option is now possible. This phenomenon, commonly referred as "*crowdsourcing*", progressively appeared through three key steps: (1) the emergence of Web 2.0 enabled the development of tools and features that ensure a continuous exchange of information between Internet users; (2) the rise of geolocation and location-based services that goes hand in hand with (3) the development of Mobile internet and smartphones, made possible the joint enrichment of spatial data. In the landmark register, Richter and Winter have developed a module that allows contributors to add tags that contain landmark information on OpenStreetMap (OSM) [56]. On the one hand, users can define an existing object as a landmark. On the other hand, if the object identified is absent from the database, users are invited to create the landmark. As noted by Richter, it is also possible to use a similar approach with Google Street View [55]. This approach helps to overcome obstacles identified by Sadeghian and Kantardzic [44] but also presents a disadvantage regarding contributors' rewards. As far as the landmark-based wayfinding is not popular, OSM users may ask themselves what kind of benefits they could make by contributing to the enrichment of landmark information.

Now, as geotagged online social content are common and easily accessible, we argue that geosocial data should be used to enhance ALDSs. Indeed, if the solutions proposed for the automatic detection of landmarks were previously centered on the Big GIS paradigm [57], we are now moving undoubtedly toward the exploitation of social tagging and folksonomy [58] to feed the databases of the next generation of ALDSs. In this context, Tomko [47] followed by Tezuka and Tanaka [48] offered approaches that represent the premise of User-Geographic Generated Content (UGGC)'s exploitation for the automatic detection of landmarks. Their methods focus on text mining applied to worldwide web documents. Unlike Elias' approach and the original model, these researchers are particularly interested in how places are *expressed* by Internet users rather than visually perceived (*i.e.*, observed). They extract what they call "cognitively significant geographic objects" (*i.e.*, objects that may serve as a landmark) by decoding the spatial context of web documents. Regarding crowdsourced data, most of solutions focus on the analysis of geotagged photos (see [59–61]). Recently, researchers used geolocated data of a location-based game to identify structural landmarks [62]. Moreover, Schwartz and Naaman claim that geosocial data streams could reveal personal and collective mental maps of cities [63]. We agree with this point of view and argue that *social location sharing* datasets generated by users of online social networks can be effectively exploited to enhance the measure of landmark semantic salience.

4. Social Location Sharing Datasets as a Reliable Source of Information for the Measure of Landmark Semantic Salience

Social Location Sharing (SLS) consists of claiming "I am/was at that place" through a *check-in*. The system of check-ins was introduced with location-based social networks (LBSNs) and is now included in most of online social networks (e.g., Facebook, Google Plus, Instagram, *etc.*). In this first section, we explain why SLS data should be used to measure the semantic salience of landmarks (LSS). The other section describes how LSS can be measured through three scores that can be calculated with Swarm and Facebook geolocated data.

4.1. Why Use Social Location Sharing Data to Measure Landmark Semantic Salience?

4.1.1. A Relevant Indicator of Places' Collective and Individual Meaning

As stated in the previous section, approaches for detecting landmarks automatically failed to include people's daily practices of Places in their measure of LSS. As a general rule, the only feasible alternative taken was to assimilate LSS to objects' historical and cultural significance. Otherwise, LSS was only *estimated* and not measured (*cf.* [52]). As the measure of LSS is obviously numerical, the main issue was to find data that reflect in the best possible way citizens' place-based practices. We argue it can now be fixed by exploiting geolocated data shared on Internet by citizens. Indeed, VGI is widely considered as the most reliable indicator of local geographic knowledge [64].

More specifically, VGI is in our opinion composed by two kinds of data: *platial* and *locational* data. Unlike platial data, spatial dimension of locational data does not take into account the place-based component. Theoretically, space is often reduced to a simple support *on* which we daily interact. According to this statement, space is an arbitrary frame of reference composed of equivalent points (*i.e.*, places). Euclidean traditional cartography and by extension locational data are based on this Cartesian vision of space. In our opinion, lots of VGI is characterized by either *primary locational data* (e.g., a building digitalized on OSM) or *secondary locational data* (e.g., a geotagged tweet which coordinate information does not match with the place mentioned in the short message). In the first case, geographic coordinates are used to locate as accurately as possible an object. In the second case, the coordinate information is automatically added to the posted content; generally because the geolocation functionality is activated on device it was sent from. But in both case, the spatial dimension of locational data is only associated with geographic metadata; *i.e.*, lat/long coordinates.

That being said, space can also be considered as a *social construct*. According to Lévy and Lussault [65], each spatial object is based on a dialogical relationship between the material sphere and the ideational sphere (*i.e.*, language, thoughts, speeches, *etc.*). Despite its intangibility, the ideational sphere must be taken into consideration, as well as the material one. Consequently, space is no longer considered as a simple container, but as a true content of the social relationship. In other words, it cannot exist without the social dimension and *vice versa*. Based on this constructivist conception of space, Lussault [66] defines spatiality as all spatial practices performed by societies' operators (individual, group of people, organization, *etc.*). The goal is to understand the way each of us interacts *with* space; and not *on* space.

Just like Elwood *et al.* [64], we support the idea that platial data allow us to access a vernacular geographical knowledge and therefore citizens' spatialities. Actually, a large part of VGI's platial datasets comes from SLS, which is an original kind of communication based on places' values and meaning; *i.e.*, a *platial communication tool*. Indeed, several studies demonstrated that users of LBSNs publish check-ins in a strategic way in order to manage their self-representation (see [10,67–70]). Before the launch of LBSNs, Barkhuus *et al.* had already shown that users of location-based services tend to boost their social image thanks to the places they mention in their posts [67]. Indeed, since everyone is able to be aware of each other's positions, users are inclined to share platial information in order to enhance their social status. This trend is also observable in the surveys of Lindqvist *et al.*, especially in the answers of the question "*Why do not you publish check-in?*" [70]. Since SLS data are fundamentally platial, extracting from them places' meaning as well as people's daily platial practices in urban area is conceivable. That is the main reason why we believe they should be considered as an essential component in the measure of landmark semantic salience.

4.1.2. Social Location Sharing Data Are Representative of Cities' Everydayness

While some researchers have reported the publication of fake check-ins (e.g., [71]), most research conducted specifically on Foursquare demonstrated that check-ins reflected daily users' activities in urban area. That is why check-ins are now considered as a reliable source of information to observe and analyze urban dynamics [11]. Thus, for example, Noulas *et al.* collected during 100 days approximately 12 million of Foursquare check-ins from 679,000 Twitter users [72]. They were able to determine spatiotemporal patterns. Regarding the time distribution of check-ins, three peaks of activity were identified during the week: (1) in the morning, when people are going to their workplaces; (2) at lunchtime when they are taking out their lunches; and finally (3) between 6 PM and 8 PM, when they are leaving their workplaces. The distribution was quite different during the weekend. Instead of those three peaks of activity, they observed a curve that describes a constant changing throughout the day, and this gradually falls from 10 PM. For Noulas *et al.* Foursquare data (now Swarm) are representative of daily users movements [72]. Moreover, Kelley's research showed that there was a correlation between the socio-economic index of a given area (socio-economic clusters were identified by a spatial autocorrelation analysis) and the content of associated Foursquare check-ins [73]. This is the reason why he argues that LBSNs users' trails reflect the inhabitants' collective memory. Bawa-Cavia analyzed and compared check-ins' distribution of London, New York and Paris [74]. He concluded that Foursquare data can be used to reveal social-spatial phenomena like *sprawl* and *segregation*. Finally, in the context of the "*Livehoods*" project, 18 million of check-ins was harvested from the Twitter API in order to identify regions that reflect "the dynamic nature of activity patterns in the lives of city inhabitants" [75] (p. 58). The sample covers several U.S. cities and the two Canadian cities of Vancouver and Montreal. Cranshaw and Yano developed an algorithm that automatically identifies neighborhood structures based on users' activity [76]. The algorithm takes into account the geographical distance between places, but also a form of "*social distance*". For example, if users publish check-ins in a given restaurant and then post other check-ins from a bar relatively close, the algorithm will group these two places in the same neighborhood structure. Cranshaw *et al.* subsequently interviewed 27 residents of Pittsburgh and found that their structures match with the interviewees' mental map [75]. These clusters should be subsequently analyzed and compared between cities. Indeed, preliminary works in this direction have already been published (see [77]).

4.1.3. User-Generated Place Databases are Appropriate for the Measure of Landmark Semantic Salience

User-Generated Place Databases (UGPDs) are spatial databases exclusively based on places and regularly updated by Internet users. Actually, Foursquare, Facebook, and Google place databases are the most popular UGPDs. Below, we list four arguments that allow us to state that UGPDs are well appropriated for the design of ALDSs:

1. First of all, online social networks' users operate a kind of "semantic filter" by adding (or not) places. Indeed, the presence of a venue inside a UGPD obviously indicates users' interests. In other words, the presence *versus* the absence of a given place constitutes a *global* semantic indicator that can be combined with additional *local* indicators, such as the number of check-ins, comments or tips published from that place.
2. Secondly, unlike locational data, check-ins are always associated with a place for which geographical coordinates are stored in a database. This principle guarantees a positional uniformity. For example, with the exception of geo-tagged tweets sent from Foursquare, two tweets published from the same place may have different geographic coordinates depending on the precision of the mobile device from which they were posted.
3. Thirdly, SLS data allow us to categorize each place according to check-ins' activities during daytime and nighttime (especially for Swarm check-ins). Thus, these data can also be used to improve the detection of semantic landmarks for the nighttime period.
4. Finally, online social networks present the advantage of providing a wide range of place categories. Unlike traditional approaches centered on the selection of buildings as landmark candidates, a platform, such as Foursquare, gives access to several types of objects, including natural items (e.g., garden or even mountains), that can also serve as landmarks. However, we must acknowledge that a large part of UGPDs are essentially composed of buildings.

That being said, some drawbacks remain. Thus, UGPDs may account fictitious places that *de facto* cannot serve as landmark candidates (e.g., [61]). Nonetheless, we would like to moderate the impact of this disadvantage since additional parameters can be taken into account (e.g., the number of distinct users who have published check-ins). The second disadvantage identified is harder to bypass. More specifically, it deals with a problem of *sets of scales*. If we consider the example of a mall: the building contains several shops and users may post their check-ins from these venues instead of the mall. However, in the context of landmark detection, the global object (*i.e.*, the Mall) should be taken into account for the landmark-based navigation instead of local objects (*i.e.*, shops located inside) since they are invisible from outside. Finally, the last inconvenience identified is related to the accuracy of places positions. Indeed, in the case of Swarm and Facebook, the position accuracy is not verified by the platform. It depends on the user who has added the venue in the database. Therefore, positioning errors may not be excluded. This being so, in the case of Swarm, "*superusers*" are supposed to check venues' location information and rectify any error if necessary.

4.1.4. Daily Footprints Left by Social Media Users can be Used to Improve the Navigation Context-Based Landmark Detection

As clearly explained by Winter *et al.* [42], people's landmarks selections are greatly influenced by the context of navigation. For instance, tourists would tend to rely on global (*i.e.*, objects that are highly visible from apart) and popular landmarks while local people might also focus on local landmarks, which are in most of cases not necessarily well known from everyone. Ideally, ALDSs route instructions should be delivered according to each traveler' spatial knowledge. But for the moment, designing such systems remains inconceivable unless users share deliberately their spatial (platial) knowledge (e.g., through a Swarm or Google Plus check-in history). The only alternative consists of providing *standard* landmark-based instructions that help *tourists* and *local* people at the same time. Therefore, in the case of semantic landmark candidates, we believe that *global semantic landmarks* should be used instead of *local semantic landmarks*. In this way, global semantic landmarks could be detected through social media, such as Swarm and Facebook using (1) the top-category level of venues (e.g., Swarm's "*Monument*/*Landmark*" category or Facebook's "*Landmark*" category); and (2) the check-in activity (*i.e.*, the more checked-in the venue is, the more it will be considered as a landmark candidate). Finally, social web platforms like Swarm are able to compute venues' popular time frames according to users' check-in activity (*cf.* "Venues Hours" of Foursquare API). We believe that this opportunity should be exploited to improve night time-based detection of landmarks. This is a determinant parameter since people's landmarks selections also depend on conditions of navigation (*i.e.*, day *versus* night) [42].

4.2. How Landmark Semantic Salience can be Measured through SLS Data Streams?

In this last sub-section, we propose three indicators that can be computed to measure the semantic salience of landmarks. These scores are associated with the statistics released by both Facebook and Foursquare's APIs. We do not include Google Plus API because it does not provide any information about check-ins. Indicators mentioned below should be used for places located at choice-points and on-route portions since references to landmarks in route instructions are higher from those areas [28].

4.2.1. Uniqueness of Venues

The notion of uniqueness in the context of landmarks detection is intrinsically linked to semantic and visual saliencies [50]. Thus, the main objective is to find the place where its *function* stands out the most compared to surrounding places. Indeed, we support the idea that, for example, a church located in a street surrounded by shops will necessarily draw a greater attention to travelers. We propose to measure the uniqueness of a given place *P* by calculating a uniqueness score *UNQ*. Given a choice-point *CP*, *UNQ* corresponds to the ratio between the total numbers of places belonging to *P*'s category and the total number of places located at *CP*; any categories combined:

$$\forall\, n, m > 1: UNQ(p) = \frac{\sum_{i=1}^{n} p_i \in C}{\sum_{j=1}^{m} p_j} \tag{1}$$

where, *UNQ* = uniqueness score, *p* = place, *C* = place's category.

Consequently, the higher the uniqueness score is, the lower the category concerned tends to stand out from the surrounding places. In order to compare UNQ with the next score, a normalization of the data from 0 to 1 is needed. An inverse normalization should be performed in the case of UNQ:

$$UNQ(p_i)_{0\ to\ 1} = 1 - \left(\frac{UNQ(p_i) - UNQ_{min}}{UNQ_{max} - UNQ_{min}}\right) \tag{2}$$

where, UNQ_{min} = the minima score among all uniqueness scores, UNQ_{max} = the maxima score among all uniqueness scores.

4.2.2. Geosocial Activity of Venues

The following score reflects users' geosocial activity generated for each venue (*cf.* Equation (3)). It represents the main indicator for the measure of landmark semantic salience. In the case of Swarm, the calculation of the geosocial activity score takes into account three specific indices: the *number of distinct users* who have published one or more check-ins from a venue, and the *number of tips* and "*likes*" linked to them. The number of distinct users is quite relevant because some venues may account a high number of check-ins generated by only few users. That is the reason why we have decided to exclude the total number of Swarm check-ins associated with a venue. Finally, the number of "likes" and tips should also be taken in consideration since Swarm users are also able to comment places where they go.

$$\forall\, m \geq 1{:}\ GSA(p)_{Swr} = USR(p) + LK(p) +\ TP(p) \tag{3}$$

where, *GSA* = geosocial activity score, *p* = place, *Swr* = Swarm, *TP* = tips, *LK* = likes, *USR* = users who have published one or more check-ins from p.

The geosocial activity score based on Facebook's data is less accurate than Swarm GSA since the Graph API does not provide a distinct number of users. Thus, we propose to measure it by calculating the arithmetic sum of check-ins, "likes" and "talking about" (*i.e.*, the count for the number of people who talk about the place on Facebook).

$$GSA(p)_{fb} = CK(p) + LK(p) + TA(p) \tag{4}$$

where, *fb* = facebook, *CK*= check-ins, *LK* = likes, *TA* = talking about count.

Just as the uniqueness score, normalization of data in the range [0;1] should be operated for the geosocial activity score. In order to detect global semantic landmarks for both visiting and local people (*cf.* Section 4.1.4), a classic normalization should be performed for both Swarm and Facebook GSA:

$$GSA(p_i)_{0\ to\ 1} = \frac{GSA(p_i) - GSA_{min}}{GSA_{max} - GSA_{min}} \tag{5}$$

where, GSA_{min} = the minima score among all geosocial activity scores, GSA_{max} = the maxima score among all geosocial activity scores.

4.2.3. Landmark Semantic Salience

We propose to measure the landmark semantic salience score of a place by summing its uniqueness and geosocial activity scores, both normalized:

$$LSS(p) = UNQ(p)_{norm} + GSA(p)_{norm} \tag{6}$$

The measure of LSS is quite easily done through Facebook and Foursquare's APIs. Indeed, it is possible to harvest all the data needed in order to calculate the various quantitative scores outlined above by logging onto the Foursquare's Venues Platform (see [78] to get an overview of the structure of check-ins collected directly via the API). Regarding Facebook, requests are simply made through Facebook Graph API v.2.1.

5. Geosocial Data-Based Semantic Landmark Detection

The last section of this article is dedicated to the detection of semantic landmarks using real social media data. We begin this exemplification section on a global scale with *world famous landmarks*, and finish it with the detection of *semantic landmarks located in the city of Vienna*. *Paris global semantic landmarks* are also studied in the second sub-section. For information, all datasets were harvested on 29 September 2014 (for the Sections 5.1 and 5.3) and on 15 November 2014 (for the Section 5.2) using Foursquare API v2 and Facebook API v2.1.

5.1. World Famous Semantic Landmarks

As a beginning, we have chosen from different countries around the world ten well-known landmarks (*cf.* Table 2). The objective here is twofold: (1) first of all, we observe the presence or the absence of each landmark selected in order to evaluate the global reliability of Facebook and Foursquare databases. Then, (2) we verify if the "*Landmark*" category ("*Monument*/*Landmark*" in the case of Foursquare) is relevant in the context of landmark detection.

As we can notice in the Table 2, all listed landmarks are present in Facebook and Foursquare databases. More specifically, it appears that Facebook categories remain more homogeneous than those ones on Foursquare. Indeed, eight of the 10 chosen landmarks belong to the Facebook "*Landmark*" category while only four venues on the list are considered as "*Monument*/*Landmark*". This can be explained not because of the variety of landmarks (both Foursquare and Facebook propose an impressive amount of venue categories), but rather because of their distinct category hierarchies. Thus, Foursquare "*Monument*/*Landmark*" belongs to the "*Government Buildings*" supra-category while Facebook's "*Landmark*" category constitutes a top-level category itself. We can suppose that Swarm users tended to look for the exact nature of the listed venues when they have added it (e.g., "Mountain") while Facebook users were directly able to associate them as a landmark. As a short conclusion, we assume that global landmarks—*i.e.*, landmark used for global orientation [30]—will mostly fall into Facebook's "Landmark" category. In addition, we have inserted geosocial activity score (GSA) of each place as complementary information. Facebook and Swarm GSA cannot be compared since they are based on different indicators (*cf.* Section 4.2.2). That being said, we can see that the Eiffel Tower remains indisputably the top-one world semantic landmark. It does make sense since France is the most visited country in the world. In the end, we can see that there is a link between users geosocial activity and venues' popularity (e.g., nearly 4 million geolocated likes, talking about, and check-ins about the Eiffel Tower on Facebook).

Table 2. Information of word popular landmarks according to Facebook and Swarm.

Landmark	Swarm Category	Swarm GSA	Facebook Category	Facebook GSA
Eiffel Tower (*France*)	Monument/Landmark	111,217	Monument	3,896,373
Golden Gate Bridge (*USA*)	Bridge	69,960	Monument	698,102
Coliseum (Italy)	Historic Site	65,159	Landmark	28,201
Statue of Liberty (USA)	Monument/Landmark	49,225	Landmark	135,036
Christ the Redeemer (*Brazil*)	Monument/Landmark	25,487	Landmark	43,796
Stonehenge (UK)	Historic Site	15,669	Landmark	479,298
Taj Mahal (India)	Historic Site	7846	Landmark	139,097
Great Pyramids of Giza (Egypt)	Historic Site	3807	Landmark	26,813
Mount Fuji (*Japan*)	Mountain	3600	Landmark	14,929
Uluru (Australia)	Monument/Landmark	793	Landmark	8176

5.2. Global Semantic Landmarks across the City of Paris

Considering what we observed previously, we can assume that the more popular a venue is, the more geosocial activity will be generated from it. In order to verify this hypothesis, we selected five popular places located across the city of Paris. These venues are usually used by tourists for global orientation (*i.e.*, global landmarks) during their visits: (1) the *Eiffel Tower*; (2) the *Arc de Triomphe*; (3) the *Place de la Concorde*; (4) the *Louvre museum*; and finally (5), the *Bibliothèque François Mitterrand* (*cf.* Figure 4). For each place mentioned above, we extracted from Foursquare database the top 5 venues located within a 500 m. circle area in order to create a list of Parisian global semantic landmarks. Circle centers correspond to each popular landmark lat/long information.

Without any surprise, the Eiffel Tower is the most popular semantic landmark on the list with a GSA of 111,217. In its associated area, the *Parc du Champs de Mars* and *Jardins du Trocadéro* green spaces appear, respectively, at the second and fifth position. Actually, the *Parc du Champs de Mars* is one of the largest parks in Paris with a surface area of 25 Ha. The *58 Tour Eiffel* restaurant, which is listed just after this park, is located inside the Eiffel Tower. Providing wayfinding instructions based on this place does not make much sense since it is invisible from outside. This is an explicit illustration of the *sets of scales* issue (*cf.* Section 4.1.3). In the end, the *Quai Branly* museum is ranked fourth with a GSA of 5684. This place is one of the best-known Parisian museums with the *Louvre*.

The Louvre museum appears in second position with a GSA score of 83,136. As we can see, its popular pyramid is also on the list (ranked third). The *Carrousel du Louvre*, which comes directly after the Louvre (GSA: 18,489), is a dynamic place since it hosts restaurants, shops, and an art exhibition hall at the same time. By the way, the *Apple Store* located inside this venue is ranked fourth. Once again, we are facing an issue of *sets of scales*. Finally, the last position is held by the *Pont des Arts*, which is a bridge registered as "*historic monument*" since 1975.

The *Arc de Triomphe* score is behind the one of the Louvre museum with a GSA of 43,865. It is interesting to note that the second and the third venues listed here are stores. On the one hand, there is the *Louis Vuitton* store (luxury leather goods), and on the other hand, there is the *Publicis Drugstore*; a famous Parisian mall characterized by its original architecture. Just like the *Charles De Gaulle Place* (previously *Place de l'étoile*), the café *George V* generates a significant GSA score of 4457.

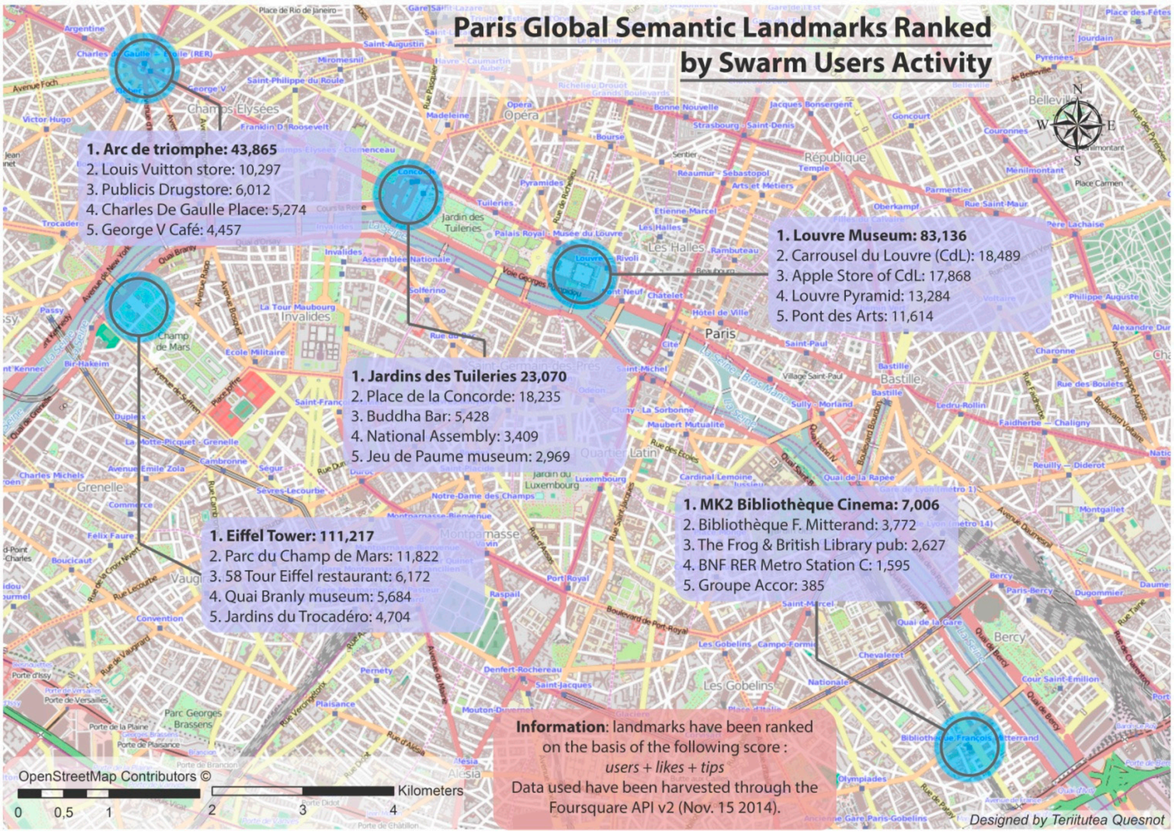

Figure 4. Paris global semantic landmarks ranked by Swarm users activity.

The pattern associated with the area of *Place de la Concorde* is quite interesting. Indeed, we can see that *Place de la Concorde* appears in second position behind the green space *Les Jardins des Tuileries*. These two venues clearly stand out from the three others in terms of geosocial activity (23,070 GSA for the *Jardins des Tuileries* and 18,235 GSA for *Place de la Concorde*). Indeed, the venue ranked third is a famous Parisian pub named *Buddha Bar* with a GSA of "only" 5428. The *National Assembly* and the museum of contemporary art *Jeu de Paume* appear, respectively, in fourth and fifth position.

Finally, the fifth example demonstrates that including a *social* component in the measure of landmark semantic salience using SLS datasets is relevant: instead of being at the supposed first place, the *Bibliothèque François Mitterrand* (BNF) stands at the second one, largely behind the cinema *MK2 Bibliothèque* (3772 GSA for the BNF *versus* almost the twice with 7006 GSA for the *MK2*). It demonstrates that a place *culturally* significant (*i.e.*, the BNF) is not necessarily *socially* meaningful; *i.e.*, daily practiced or recognized by citizens. By the way, we can see that the GSA score of *The Frog & British Library* pub is close to the BNF's one (2627). Actually, the MK2 is the most relevant semantic landmark because it remains the unique movie theater located in the BNF region, which is an area characterized by a massive amount of offices. That is the reason why the *Groupe Accor* (a hostel operator) and the *BNF RER Metro Station C* also appear on the list.

5.3. Detecting Landmarks in the Streets of Vienna (Austria)

To conclude this final section, we propose five scenarios that take place in the city of Vienna. By this way, we want to demonstrate that the Landmark Semantic Salience score (LSS) proposed in the

Subsection 4.2.3 is reliable to extract global semantic landmarks for navigation. Each scenario deals with an intersection—*i.e.*, a choice point area [29]—where travelers can select different landmarks depending on the itinerary chosen. The first scenario takes place at the intersection of the streets *Philarmonikerstraße* and *Kärntner Straße*, near the Opera of Vienna. As shown in the Figure 5, we can identify four potential landmark candidates given the three itineraries proposed (*i.e.*, A–C): (1) the *Opera of Vienna*, (2) the *Starbucks Coffee* and (3) the *Café Sacher*, a well-known and prestigious Viennese café, and (4), a clothing store named *Popp & Kretschmer*. Given their popularity, the Opera of Vienna and the two coffee shops should generate a lot of geosocial activity. The Table 3 summarizes the GSA and uniqueness scores both normalized, as well as the LSS (*i.e.*, the arithmetic sum of GSA and uniqueness normalized scores) associated with places located at the first intersection.

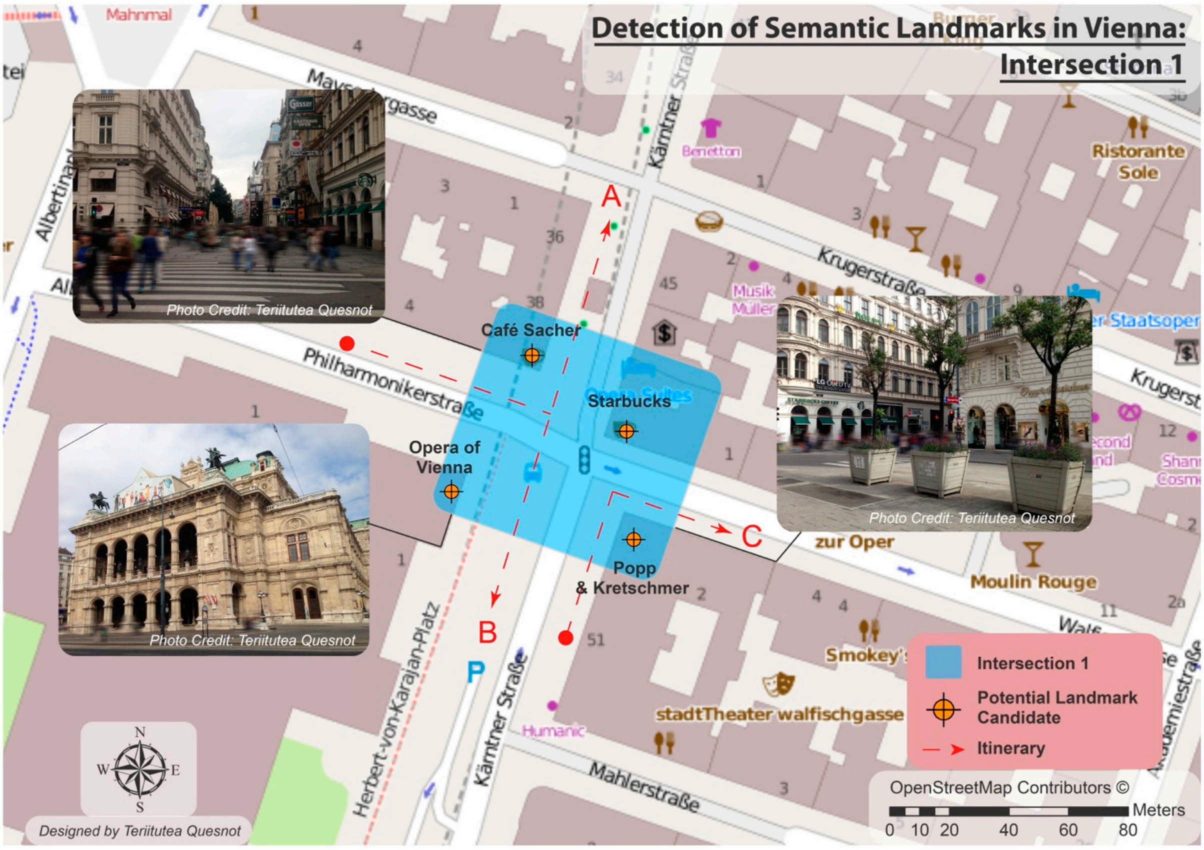

Figure 5. Detection of Semantic Landmarks in Vienna at the intersection 1.

Table 3. Landmark semantic salience measured for places located at the intersection 1.

Landmark	Swarm GSA (n)	Facebook GSA (n)	Uniqueness (n)	LSS (Swarm)	LSS (Facebook)
Vienna Opera	0.72	1	1	1.72	2
Café Sacher	1	0.29	0	1	0.29
Starbucks	0.50	0.02	0	0.50	0.02
Popp & Kretschmer	0	ABS	1	1	NA

As we can see, the Opera of Vienna does not necessarily generate the highest GSA in both platforms. Café Sacher appears to be more popular than the opera on Swarm. However, because of its uniqueness, the Opera of Vienna remains undoubtedly the top-one semantic landmark located at this intersection. Since Starbucks and Café Sacher are both cafés, their uniqueness score is reduced to 0. Popp & Kretschmer is the unique clothing store but it generates the lowest GSA. Plus, this venue is absent from the Facebook place database. That is the reason why it is ranked at the last position. Regarding the itinerary A, the Starbucks and the Café Sacher are potential landmark candidates unlike the Opera of Vienna and Popp & Kretschmer, which have in this context a weak structural salience (*i.e.*, an unfavorable position). According to their respective LSS, the Café Sacher is considered as a landmark candidate. In the same vein, the Opera of Vienna and the Starbucks are, respectively, landmark candidates for itineraries B and C.

The intersection 2 is located along the street *Kärntner Straße*, near the *Stephansplatz* metro station. In this second scenario, four places could be used as a landmark: (1) the *Swarovski* store; (2) the pizzeria *Venezia* and (3,4), the clothing stores *Forever 21* and *Esprit* (*cf.* Figure 6). Unsurprisingly, the popular Swarovski store is the most reliable semantic landmark associated with this intersection according to our LSS calculation (*cf.* Table 4). It is the unique jewelry store located there and it has the highest GSA in both platforms. Actually, this place could be used as a landmark candidate for both itineraries D and E. Venezia appears in second position: it does not generate a great GSA but it is the only pizzeria situated at the intersection. Thus, it has also a uniqueness score of 1. Forever 21 and Esprit are both clothing stores and consequently get their uniqueness score reduced to 0. Their LSS are very low since they generate weak GSA scores. That being said, in the case of the itinerary E, the Forever 21 store could be favored because of its advantageous position (structural salience).

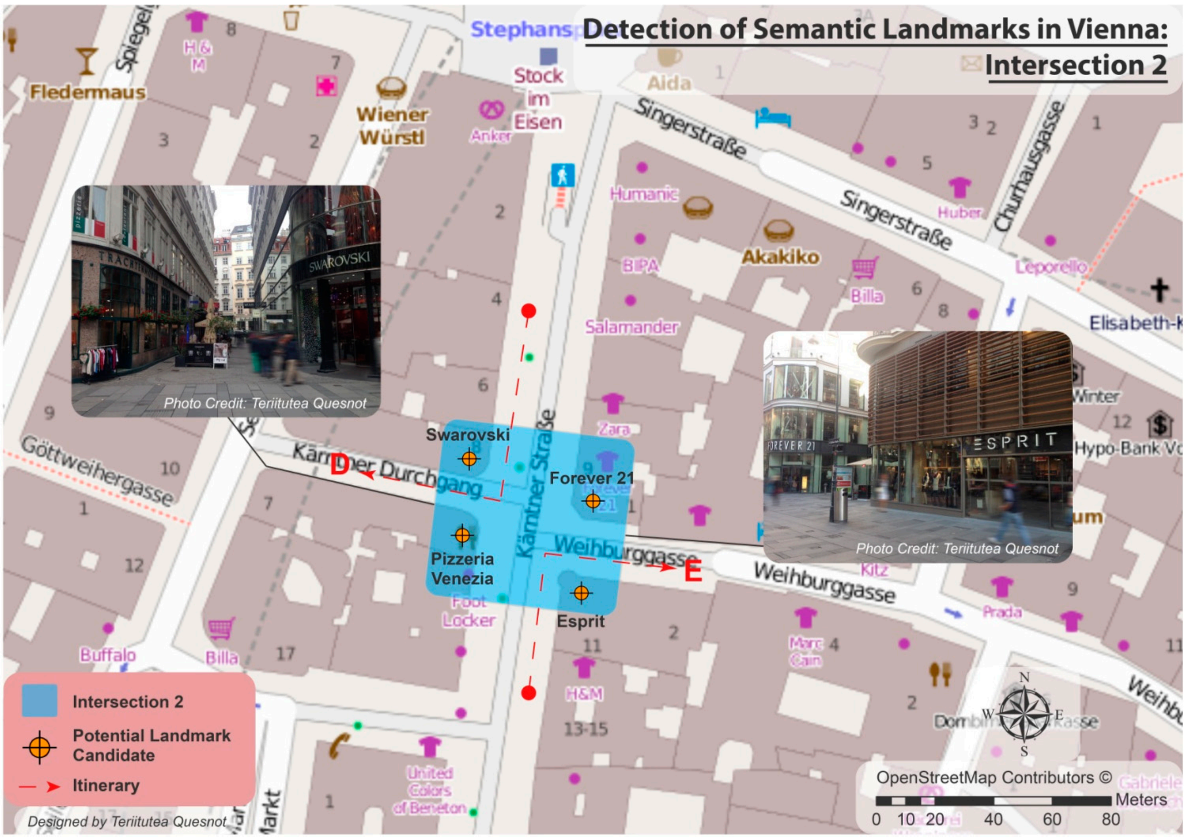

Figure 6. Detection of Semantic Landmarks in Vienna at the intersection 2.

Table 4. Landmark semantic salience measured for places located at the intersection 2.

Landmark	Swarm GSA(n)	Facebook GSA(n)	Uniqueness (n)	LSS (Swarm)	LSS (Facebook)
Swarovski	1	1	1	2	2
Pizzeria Venezia	0.25	0.02	1	1.25	1.02
Forever 21	0.30	0.01	0	0.30	0.01
Esprit	0	ABS	0	0	NA

Table 5. Landmark semantic salience measured for places located at the intersection 3.

Landmark	Swarm GSA(n)	Facebook GSA(n)	Uniqueness (n)	LSS (Swarm)	LSS (Facebook)
Aida Cafe	1	1	NA	1	1
Humanic (Clothing)	0.11	ABS	NA	0.11	NA
Jeweler Bucherer	0	ABS	NA	0	NA

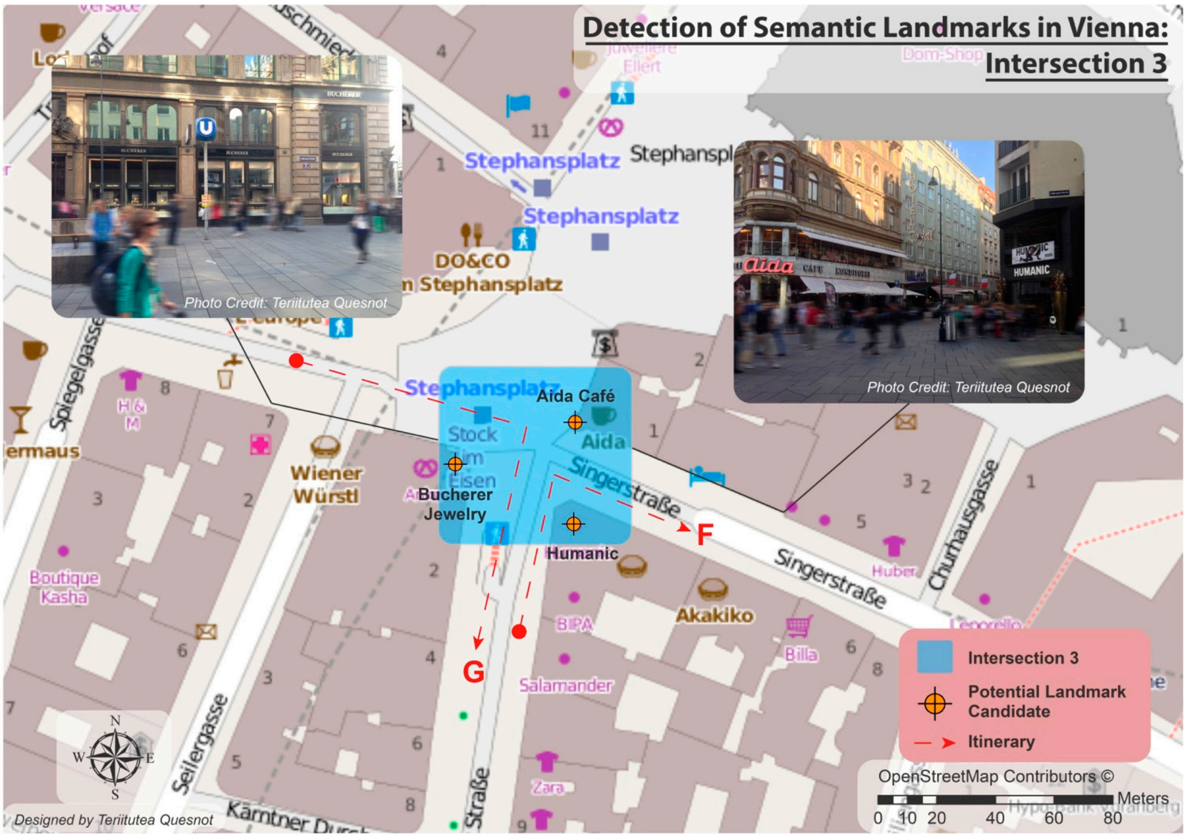

Figure 7. Detection of Semantic Landmarks in Vienna at the intersection 3.

The third scenario takes place at the junction of the streets *Kärntner Straße* and *Singerstraße*. We distinguish here three potential landmark candidates: (1) *Aida Café*; (2) *Humanic*; and (3) *Bucherer*. In this example, the calculation of the uniqueness score is not relevant since the three places mentioned above do not belong to the same category. Indeed, there is a coffee house (*Aida Café*), a clothing store (*Humanic*), and a jewelry store (*Bucherer*). According to our LSS calculation, the Aida café, a famous Viennese coffee shop, is the most relevant semantic landmark located at this intersection. This café is full of consumers on a daily basis. Actually, we can consider it as a landmark candidate for both itineraries F and G because (1) Humanic and Bucherer produce a weak GSA and are absents from Facebook database (*cf.* Table 5); and (2) this coffee shop is highly visible (*cf.* Figure 7).

The next intersection is located at the junction of the streets *Graben* and Spiegelgasse. It concerns three potential landmarks: (1) the *Nespresso* store; (2) the *H&M* store; and (3) the *Altmann & Kühne* candy shop (*cf.* Figure 8). Once again, the calculation of the uniqueness score is not pertinent since we identified three different kinds of place categories.

Figure 8. Detection of Semantic Landmarks in Vienna at the intersection 4.

As shown in the Table 6, Nespresso and H&M can be used as landmark candidates. Indeed, Nespresso only gets the highest Swarm LSS while H&M holds the greatest value for Facebook LSS. In fact, the discrimination is neither semantic nor structural but visual. In our opinion, Nespresso should be the landmark candidate for the itinerary H because unlike the H&M store, its signboard is highly visible from a long distance (*cf.* photo in Figure 8).

Table 6. Landmark semantic salience measured for places located at the intersection 4.

Landmark	Swarm GSA(n)	Facebook GSA(n)	Uniqueness (n)	LSS (Swarm)	LSS (Facebook)
Nespresso	1	0.32	NA	1	0.32
H&M	0.28	1	NA	0.28	1
Altmann & Kühne	0	ABS	NA	0	NA

The last scenario, which takes place at the intersection of the streets *Graben* and *Braunerstraße*, reveals a quite interesting element. In this case, four places are potential semantic landmarks (*cf.* Figure 9): (1) the clothing store *Palmers*; (2) the *Pestsäule* (Plague Column); (3) the *Heldwein* jewelry store; and (4) a *Starbucks* store. According to our LSS calculation (*cf.* Table 7), Palmers and Heldwein are excluded because of their very low GSA scores. The Pestsäule appears in second position, far behind the Starbucks store (0.01 *versus* 1 regarding the Facebook LSS). The Pestsäule is a monument with a great historical and cultural significance. Yet, it is odds-on that tourists who follow the itinerary I would easily find their way with a semantic landmark, such as the Starbucks. Indeed, they do not necessarily know what the Plague Column is and what it does look like. Just like the BNF and MK2 example of the Section 5.2, this scenario illustrates that people are not necessarily based on a place historically and culturally important. By extension, a place that benefits from a great historical or cultural significance does not systematically imply that it is a reliable semantic landmark. That being said, in the case of the itinerary J, selecting the Pestsäule as the landmark candidate would be more relevant since the Starbucks is completely invisible from this direction (weak visual salience).

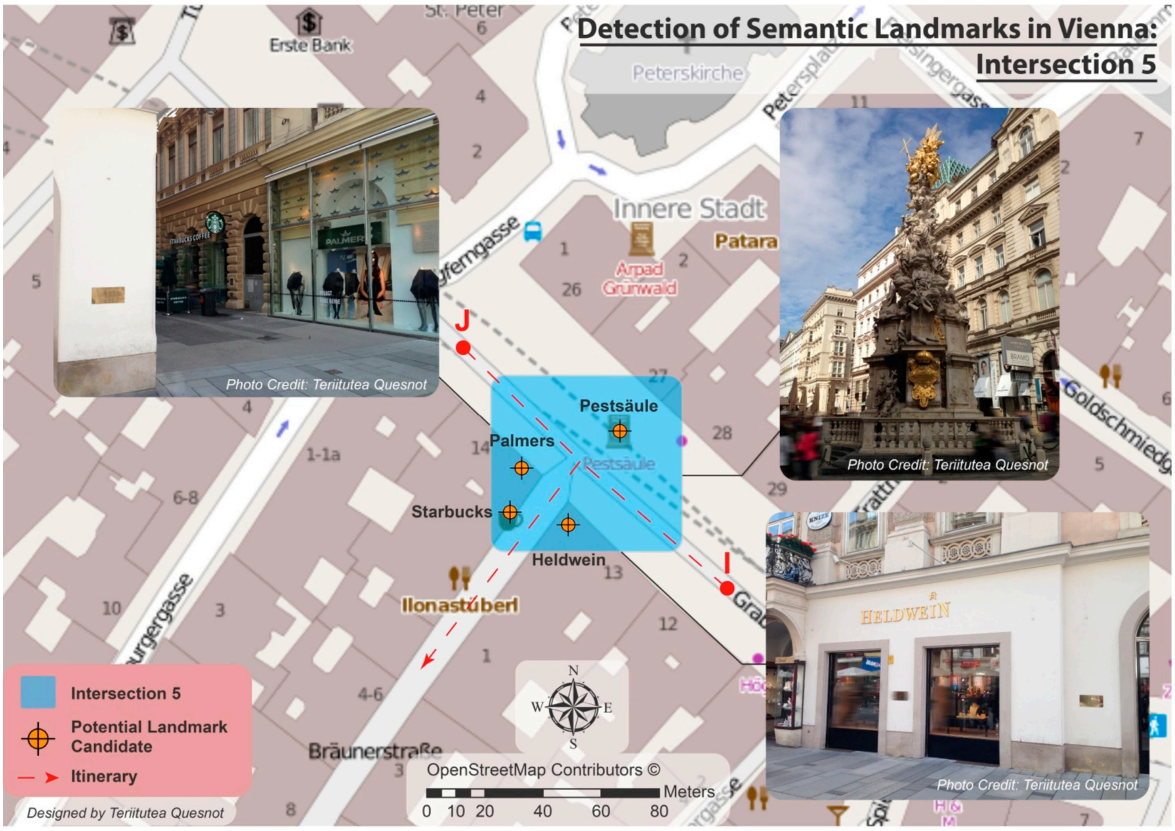

Figure 9. Detection of Semantic Landmarks in Vienna at the intersection 5.

Table 7. Landmark semantic salience measured for places located at the intersection 5.

Landmark	Swarm GSA(n)	Facebook GSA(n)	Uniqueness (n)	LSS (Swarm)	LSS (Facebook)
Starbucks	1	1	NA	1	1
Pestsäule	0.21	0.01	NA	0.21	0.01
Heldwein	0	0	NA	0	0
Palmers	0.004	ABS	NA	0.004	NA

5.4. Discussion and Outlook

Three elements need to be discussed in this last sub-section. The first one is tied down to the calculation of the uniqueness score (UNQ). Indeed, it was computed by taking into account the bottom-level venue categories of the potential landmark candidates. For example, in the case of the first scenario, the Swarm LSS of the clothing store Popp & Kretschmer is higher than the one from the Starbucks coffee, thanks to its uniqueness scores (*cf.* Table 3). The two cafés and the clothing store were considered different in the computation of UNQ. This approach implies that these two venue categories are easily distinguishable in a navigation context; which is not necessarily the case. Actually, the Opera of Vienna is in our opinion the only feature that stands out by its function in the area of the intersection 1. The others potential landmark candidates are essentially stores. Consequently, as an improvement, we do believe that the uniqueness score proposed could be graded depending on the top-level venue categories. In this way, the degree of dissimilarity would be higher if the places compared together do not belong to the same top-level category (e.g., stores *versus* a monument like the Opera of Vienna) and *vice versa*. By extension, features that do not belong to the same infra-level venue category (e.g., a jewelry store *versus* a clothing store) inside an identical supra-level venue category (e.g., stores) might be considered dissimilar, but not in an exclusive way. As an example, the pizzeria Venezia located at the intersection 2 would have the highest uniqueness score (*i.e.*, 1) since it remains the only restaurant in the area. On the other hand, we would assign a graded uniqueness score to the three other places (e.g., 0.5 for the Swarovski jewelry store, and 0.25 for both Forever 21 and Esprit clothing stores). This question, which is not solved in this paper, gives some central themes for further research in the area of automatic landmark detection.

Secondly, we have seen that places known as historically and culturally significant do not systematically generate the highest activity on online social networks. Indeed, as highlighted in the Section 5.2, the GSA score of the MK2 movie theater is higher than the one of Paris BNF. We made a similar observation for the Buddha bar and the National Assembly (5428 *versus* 3409) as well as the Louis Vuitton store and the Place Charles de Gaulle (10,297 *versus* 5274). Therefore, in our opinion, computing a landmark semantic salience score exclusively based on the *historical and cultural significance* attribute is not relevant. Including places' social dimension through the exploitation of SLS datasets will undoubtedly enhance the measure of landmark semantic salience. Furthermore, we are asking the following question: considering the last scenario, is the *Plague Column* a better semantic landmark than the *Starbucks coffee*? Actually, we can assume that the *Starbucks* brand is more popular than the *Plague Column* but this question does not make much sense since the selection of landmarks is permanently route-dependent. As we explained, choosing the Starbucks as the landmark candidate is only appropriate for the itinerary I. Indeed, a pedestrian will not be able to see the coffee house if he follows the itinerary J (*cf.* Figure 9).

This statement leads us to the third element that we want to highlight here: the detection of landmarks cannot be exclusively done on the basis of their semantic salience. Obviously, the potential landmark candidates have to be enough visible in order to be useful in a navigation context (*cf.* Winter's work on advance visibility [41]). Now, considering two places visually comparable (*i.e.*, with a visual salience score equivalent), the selection of the landmark candidate will depend on their respective structural salience; especially their position relative to the road. More specifically, places located where the next turn is supposed to be performed will tend to draw a greater attention to travelers [52]. Consequently, how semantic salience is decisive for people's landmarks selection? Actually, we argue that the significance of landmark semantic salience compared with visual and structural saliencies depends on two interrelated factors: (1) the traveler's profile; and (2) the intensity of the landmark semantic salience itself. Indeed, on the one hand, we can assume that a tourist will tend to rely on highly visual and structural landmarks (e.g., a building with an outstanding architecture located at a major road intersection) unless he sees a place that sounds familiar to him; *i.e.*, a global semantic landmark, such as a Starbucks coffee. On the other hand, an individual who is travelling in a familiar environment will easily find his way through both global and local semantic landmarks (*i.e.*, places not necessarily famous). Thus, unless we have access to each traveler's spatial knowledge, only *global* semantic landmarks should be added in *standard* route instructions. This assumption needs to be empirically tested out since the semantic salience of landmarks remains a theory-based suggestion.

6. Conclusions

Designing landmark-based navigation systems is more newsworthy than ever. It has been over a decade since research in spatial cognition has demonstrated that incorporating landmarks in route instructions improved significantly human wayfinding, particularly for pedestrians. However, none of the major route platforms, such as Google Maps and Yahoo Maps, provides this functionality. The only service that offered landmarks-based verbal instructions was *whereis* [52]. The algorithm implemented on this platform *estimated* the salience of landmarks by relying on the top-level categories to which buildings belong, instead of focusing on their individual characteristics (e.g., height, color, *etc.*). Actually, two main drawbacks are associated with this approach. On the one hand, it is based on the exploitation of points of interest (POIs) database while landmarks are not limited to POIs [79]. On the other hand, due to a lack of relevant data, visual and structural saliencies of landmarks were systematically privileged at the expense of semantic salience. More precisely, in the context of automatic landmark detection, *historical and cultural significance* remains an attribute generally used to characterize the landmark semantic salience. Nevertheless, as we aimed at demonstrating through the last section of this article: (1) user-generated place databases (e.g., Swarm) are broader than POIs databases and their associated statistics, such as *Swarm check-ins* and *Facebook talk about,* are currently the most appropriate VGI data for the detection of *global* semantic landmarks; (2) A place with a highly historical and cultural significance is not necessarily well practiced and recognized by people. Therefore, that is the reason why we argue in the end that this indicator should be completed by places' social dimension encapsulated in geosocial data streams.

Acknowledgments

This research is funded by the Social Sciences and Humanities Research Council of Canada (SSHRC). Figures' base map has been extracted from the database of OpenStreetMap (OSM). OSM Data are available under the Open Database License (www.opendatacommons.org/licenses/odbl). In the end, we would like to sincerely thank the reviewers for their insightful comments. Their reviews helped us to significantly improve this article.

Author Contributions

Teriitutea Quesnot has formalized the semantic salience scores (UNQ, GSA and LSS), harvested Facebook and Swarm data, and wrote the manuscript under the supervision of Stéphane Roche.

Conflicts of Interest

The authors declare no conflict of interest.

References

1. Calabrese, F.; Colonna, M.; Lovisolo, P.; Parata, D.; Ratti, C. Real-time urban monitoring using cell phones: A case study in Rome. *IEEE Trans. Intell. Transp. Syst.* **2011**, *12*, 141–151.
2. Calabrese, F.; Kloeckl, K.; Ratti, C. Wikicity: Real-time location-sensitive tools for the city. *Handb. Res. Urban Infor.* **2008**, 390–413.
3. Calabrese, F.; Pereira, F.C.; Di Lorenzo, G.; Liu, L.; Ratti, C. The geography of taste: Analyzing cell-phone mobility and social events. *Pervasive Comput*. **2010**, doi:10.1007/978-3-642-12654-3_2.
4. Ratti, C.; Sevtsuk, A.; Huang, S.; Pailer, R. Mobile landscapes: Graz in real time. In *Location Based Services and Telecartography*; Springer: New York, NY, USA, 2007; pp. 433–444.
5. Ratti, C.; Williams, S.; Frenchman, D.; Pulselli, R. Mobile landscapes: Using location data from cell phones for urban analysis. *Environ. Plan. B* **2006**, *33*, 727–748.
6. Reades, J.; Calabrese, F.; Sevtsuk, A.; Ratti, C. Cellular census: Explorations in urban data collection. *IEEE Pervasive Comput.* **2007**, *6*, 30–38.
7. Goodchild, M.F. Citizens as sensors: The world of volunteered geography. *Geo J.* **2007**, *69*, 211–221.
8. Exner, J.; Hemsley, J. Urban monitoring laboratory: New benefits and potential for urban planning through the use of urban sensing, geo- and mobile-web. In *Real CORP Proceedings*; Competence Center of Urban and Regional Planning: Essen, Germany, 2011; pp. 1087–1096.
9. Crampton, J.; Graham, M.; Poorthuis, A.; Shelton, T.; Stephens, M.; Wilson, M.W.; Zook, A.M. Beyond the geotag: situating 'big data' and leveraging the potential of the geoweb. *Cartogr. Geogr. Inf. Sci.* **2013**, *40*, 130–139.
10. Tang, K.P.; Lin, J.; Hong, J.I.; Siewiorek, D.P.; Sadeh, N. Rethinking location sharing: Exploring the implications of social-driven *vs.* purpose-driven location sharing. In Proceedings of UbiComp 2010, Copenhagen, Denmark, 26–29 September 2010.
11. Thatcher, J. Living on fumes: Digital footprints, data fumes, and the limitations of spatial big data. *Int. J. Commun.* **2014**, *8*, 1765–1783.
12. Giffinger, R.; Fertner, C.; Kramar, H.; Kalasek, R.; Pichler-Milanovic, N.; Meijers, E. *Smart Cities: Ranking of European Medium-Sized Cities, Centre of Regional Science (SRF)*; Vienna University of Technology: Vienna, Austria, 2007.
13. Chourabi, H.; Nam, T.; Walker, S.; Gil-Garcia, J.R.; Mellouli, S.; Nahon, K.; Pardo, T.; Scholl, H.J. Understanding smart cities: An integrative framework. In Proceedings the of 45th Hawaii International Conference on System Sciences, Maui, HI, USA, 4–7 January 2012.
14. Batty, M. *The New Science of Cities*; The MIT Press: Cambridge, MA, USA, 2013.

15. Roche, S. Geographic Information Science I: Why does a smart city need to be spatially enabled? *Progr. Hum. Geogr.* **2013**, doi:10.1177/0309132513517365.
16. Farr, A.C.; Kleinschmidt, T.; Yarlagadda, P.; Mengersen, K. Wayfinding: A simple concept, a complex process. *Transport. Rev.* **2012**, *32*, 715–743.
17. Lynch, K. *The Image of the City*; MIT Press: Cambridge, UK, 1960.
18. Downs, R.M.; Stea, D. Cognitive maps and spatial behavior: Process and product. In *Image and Environment*; Stea, D., Downs, R.M., Eds.; Aldine Publishing: Chigao, IL, USA, 1973; pp. 8–26.
19. Golledge, R.G. Human wayfinding and cognitive maps. In *Wayfinding Behavior: Cognitive Mapping and Other Spatial Processes*; Golledge, R.G., Ed.; Johns Hopkins University Press: Baltimore, MD, USA, 1999; pp. 5–45.
20. Montello, D.R.; Raubal, M. Functions and applications of spatial cognition. In *The APA Handbook of Spatial Cognition*; Waller, D., Nadel, L., Eds.; American Psychological Association: Washington, DC, USA, 2013; pp. 555–591.
21. Davies, C.; Li, C.; Albrecht, J. Human understanding of space. In *Interacting with Geospatial Technologies*; Haklay, M.M., Ed.; John Wiley & Sons Ltd.: Chichester, UK, 2010; pp. 19–35.
22. Kitchin, R.; Blades, M. *The Cognition of Geographic Space*; Tauris: London, UK, 2002.
23. Siegel, A.W.; White, S.H. The development of spatial representations of large scale environments. In *Advances in Child Development and Behavior*; Reese, W.H., Ed.; Academic Press: New York, NY, USA, 1975.
24. Ishikawa, T.; Nakamura, U. Landmark selection in the environment: Relationships with object characteristics and sense of direction. *Spat. Cogn. Comput.* **2012**, *12*, 1–22.
25. Schroder, C.J.; Mackaness, W.A.; Gittings, B.M. Giving the “right” route directions: The requirements for pedestrian navigation systems. *Trans. GIS* **2011**, *15*, 419–438.
26. Montello, D.R. A new framework for understanding the acquisition of spatial knowledge in large-scale environments. In *Spatial and Temporal Reasoning in Geographic Information Systems*; Egenhofer, M.J., Golledge, R.G., Eds.; Oxford University Press: New York, NY, USA, 1998; pp. 143–154.
27. Denis, M.; Fernandez, G. The processing of landmarks in route directions. In *Representing Space in Cognition: Interrelations of Behaviour, Language, and Formal Models*; Tenbrink, T., Wiener, J., Claramunt, C., Eds.; Oxford University Press: Oxford, UK, 2013; pp. 42–55.
28. Denis, M.; Michon, P.E.; Tom, A. Assisting pedestrian wayfinding in urban settings: Why references to landmarks are crucial in direction-giving. In *Applied Spatial Cognition: From Research to Cognitive Technology*; Allen, G.L., Ed.; Lawrence Erlbaum: Mahwah, NJ, USA, 2007; pp. 25–51.
29. Daniel, M.-P.; Denis, M. Spatial descriptions as navigational aids: A cognitive analysis of route directions. *Kognitionswissenschaft* **1998**, *7*, 45–52.
30. Lovelace, K.L.; Hegarty, M.; Montello, D.R. Elements of good route directions in familiar and unfamiliar environments. In *Spatial Information Theory*; Freksa, C., Mark, D., Eds.; Springer: Berlin, Germany, 1999; Volume 1661, pp. 65–82.
31. Denis, M.; Pazzaglia, F.; Cornoldi, C.; Bertolo, L. Spatial discourse and navigation: An analysis of route directions in the city of Venice. *Appl. Cogn. Psychol.* **1999**, *13*, 145–174.

32. Denis, M. The description of routes: A cognitive approach to the production of spatial discourse. *Cah. Psychol. Cogn.* **1997**, *16*, 409–458.
33. Michon, P.E.; Denis, M. When and why referring to visual landmarks in direction giving? In *Spatial Information Theory*; Goos, G., Hartmanis, J., van Leeuwen, J., Eds.; Springer: Berlin, Germany, 2001; Volume 2205, pp. 292–305.
34. Tom, A.; Denis, M. Referring to landmark or street information in route directions: What difference does it make? In *Spatial Information Theory*; Kuhn, W., Worboys, M.F., Timpf, S., Eds.; Springer: Berlin, Germany, 2003; Volume 2825, pp. 362–374.
35. Daniel, M.-P.; Tom, A.; Manghi, E.; Denis, M. Testing the value of route directions through navigational performance. *Spat. Cogn. Comput.* **2003**, *3*, 269–289.
36. Daniel, M.-P.; Denis, M. The production of route directions: Investigating conditions that favour conciseness in spatial discourse. *Appl. Cogn. Psychol.* **2004**, *18*, 57–75.
37. Golledge, R.G.; Dougherty, V.; Bell, S. Acquiring spatial knowledge: Survey *versus* route based knowledge in unfamiliar environments. *Ann. Assoc. Am. Geogr.* **1995**, *85*, 134–158.
38. Sorrows, M.E.; Hirtle, S.C. The nature of landmarks for real and electronic spaces. In *Spatial Information Theory Cognitive and Computational Foundations of Geographic Information Science*; Springer: Heidelberg, Germany, 1999; pp. 37–50.
39. Raubal, M.; Winter, S. Enriching wayfinding instructions with local landmarks. In *Geographic Information Science*; Egenhofer, M.J., Mark, D.M., Eds.; Springer: Berlin, Germany, 2002; Volume 2478, pp. 243–259.
40. Nothegger, C.; Winter, S.; Raubal, M. Selection of salient features for route directions. *Spat. Cogn. Comput.* **2004**, *4*, 113–136.
41. Winter, S. Route adaptive selection of salient features. In *Spatial Information Theory*; Kuhn, W., Worboys, M.F., Timpf, S., Eds.; Springer: Heidelberg, Germany, 2003; Volume 2825, pp. 349–361.
42. Winter, S.; Raubal, M.; Nothegger, C. Focalizing measures of salience for wayfinding. In *Map-Based Mobile Services*; Springer: Heidelberg, Germany, 2005; pp. 125–139.
43. Klippel, A.; Winter, S. Structural salience of landmarks for route directions. In *Spatial Information Theory*; Cohn, A.G., Mark, D.M., Eds.; Springer: Ellicottville, NY, USA, 2005; Volume 3693, pp. 347–362.
44. Sadeghian, P.; Kantardzic, M. The new generation of automatic landmark detection systems: Challenges and guidelines. *Spat. Cogn. Comput.* **2008**, *8*, 252–287.
45. Elias, B. Extracting landmarks with data mining methods. In *Spatial Information Theory*; Kuhn, W., Worboys, M.F., Timpf, S., Eds.; Springer: Berlin, Germany, 2003; Volume 2825, pp. 398–412.
46. Winter, S.; Tomko, M.; Elias, B.; Sester, M. Landmark hierarchies in context. *Environ. Plan. B* **2008**, *35*, 381–398.
47. Tomko, M. Case study—Assessing spatial distribution of web resources for navigation services. In Proceedings of the 4th International Workshop on Web and Wireless Geographical Information Systems W2GIS04, Koyang, Korea, 26–27 November 2004.
48. Tezuka, T.; Tanaka, K. Landmark extraction: A web mining approach. In *Spatial Information Theory*; Springer: Heidelberg, Germany, 2005; Volume 3693, pp. 379–396.

49. Caduff, D.; Timpf, S. The landmark spider: Representing landmark knowledge for wayfinding tasks. In Proceedings of AAAI Spring Symposium: Reasoning with Mental and External Diagrams: Computational Modeling and Spatial Assistance, Palo Alto, CA, USA, 23–25 March 2005; pp. 30–35.
50. Elias, B.; Sester, M. Incorporating landmarks with quality measures in routing procedures. In *Geographic Information Science 2006*; Raubal, M., Miller, H.J., Frank, A.U., Goodchild, M.F., Eds.; Springer: Berlin, Germany, 2006; Volume 4197, pp. 65–80.
51. Richter, K.F.; Klippel, A. Before or after: prepositions in spatially constrained systems. In *Spatial Cognition V*; Barkowsky, T., Knauff, M., Ligozat, G., Montello, D.R., Eds.; Springer: Berlin, Germany, 2007; Volume 4387, pp. 453–469.
52. Duckham, M.; Winter, S.; Robinson, M. Including landmarks in routing instructions. *J. Locat. Based Serv.* **2010**, *4*, 28–52.
53. Klippel, A.; Hansen, S.; Richter, K.F.; Winter, S. Urban granularities—A data structure for cognitively ergonomic route directions. *Geoinformatica* **2009**, *13*, 223–247.
54. Hirtle, S.C. *Geographical Design: Spatial Cognition and Geographical Information Science*; Morgan & Claypool Publishers: San Rafael, CA, USA, 2011.
55. Richter, K.F. Prospects and challenges of landmarks in navigation services. In *Cognitive and Linguistic Aspects of Geographic Space*; Raubal, M., Mark, D.M., Frank, A.U., Eds.; Springer: Heidelberg, Germany, 2013; pp. 83–97.
56. Richter, K.F.; Winter, S. Harvesting user-generated content for semantic spatial information: The Case of landmarks in OpenStreetMap. In Proceedings of the Surveying & Spatial Sciences Biennial Conference, Wellington, New Zealand, 21–25 November 2011; pp. 75–86.
57. Frank, A.U.; Raubal, M. GIS education today: From GI science to GI engineering. *URISA J.* **2001**, *13*, 5–10.
58. Trant, J. Studying social tagging and folksonomy: A review and framework. *J. Digit. Infor.* **2009**, *10*, No.1. Available online: https://journals.tdl.org/jodi/index.php/jodi/article/view/269/278 (accessed on 24 June 2014).
59. Crandall, D.; Backstrom, L.; Huttenlocher, D.; Kleinberg, J. Mapping the World's photos. In Proceedings of the 18th International Conference on World Wide Web, Madrid, Spanish, 20–24 April 2009.
60. Hile, H.; Vedantham, R.; Cuellar, G.; Liu, A.; Gelfand, N.; Grzeszczuk, R.; Borriello, G. Landmark-based pedestrian navigation from collections of geotagged photos. In Proceedings of the 7th International Conference on Mobile and Ubiquitous Multimedia, Umea, Sweden, 3–5 December 2008; pp. 145–152.
61. Schlieder, C.; Matyas, C. Photographing a city: An analysis of place concepts based on spatial choices. *Spat. Cogn. Comput.* **2009**, *9*, 212–228.
62. Jordan, K.O.; Sheptykin, I.; Gruter, B.; Vatterrott, H. Identification of structural landmarks in a park using movement data collected in a location-based game. In Proceedings of SIGSPATIAL COMP'13, Orlando, FL, USA, 5–8 November 2013.
63. Schwartz, R.; Naaman, M. Collective and individual mental maps of the city in social awareness streams. In Proceedings of GeoHCI Workshop at CHI 2013, Paris, France, 27–28 April 2013.

64. Elwood, S.; Goodchild, M.F.; Sui, D.S. Prospects for VGI research and the emerging fourth paradigm. In *Crowdsourcing Geographic Knowledge*; Sui, D.S., Elwood, S., Goodchild, M.F., Eds.; Springer Netherlands: Dordrecht, The Netherlands, 2013; pp. 361–375.
65. Lévy, J.; Lussault, M. Espace. In *Dictionnaire de la Géographie et de L'espace des Sociétés*; Belin: Paris, France, 2003; pp. 325–333.
66. Lussault, M. *L'homme Spatial: la Construction Sociale de L'espace Humain*; Seuil: Paris, France, 2007.
67. Barkhuus, L.; Brown, B.; Bell, M.; Hall, M.; Sherwood, S.; Chalmers, M. *From Awareness to Repartee: Sharing Location within Social Groups*, *CHI'08*; ACM Publishing: Florence, Italy, 2008.
68. Cramer, H.; Rost, M.; Holmquist, L.E. Performing a check-in: Emerging practices, norms and "conflicts" in location-sharing using foursquare. In Proceedings of Mobile HCI 2011, Stockholm, Sweden, 30 August–2 September 2011.
69. Evans, L. Location-based services: Transformation of the experience of space. *J. Locat. Based Serv.* **2011**, *5*, 242–260.
70. Lindqvist, J.; Cranshaw, J.; Wiese, J.; Hong, J.I.; Zimmerman, J. I'm the mayor of my house: Examining why people use foursquare—A social-driven location sharing application. In Proceedings of the Conference on Human Factors in Computing Systems (CHI-11*)*, Vancouver, BC, Canada, 7–12 May 2011.
71. Rost, M.; Barkhuus, L.; Cramer, H.; Brown, B. Representation and communication: Challenges in interpreting large social media datasets. In Proceedings of CSCW '13, San Antonio, TX, USA, 23–27 February 2013.
72. Noulas, A.; Scellato, S.; Mascolo, C.; Pontil, M. An empirical study of geographic user activity patterns in Foursquare. In Proceedings of the Fifth International AAAI Conference on Weblogs and Social Media, Barcelona, Spain, 17–21 July 2011.
73. Kelley, M.J. The emergent urban imaginaries of geosocial media. *Geo J.* **2013**, *78*, 181–203.
74. Bawa-Cavia, A. Sensing the urban: Using location-based social network data in urban analysis. In Proceedings of the Ninth International Conference on Pervasive Computing, Workshop on Pervasive Urban Applications (PURBA), San Francisco, CA, USA, 12 June 2011.
75. Cranshaw, J.; Schwartz, R.; Hong, J.I.; Sadeh, N. The Livehoods project: Utilizing social media to understand the dynamics of a city. In Proceedings of the Sixth International AAAI Conference on Weblogs an Social Media (ICWSM-12), Dublin, UK, 4–7 June 2012.
76. Cranshaw, J.; Yano, T. Seeing a home away from the home: Distilling proto-neighborhoods from incidental data with latent topic modeling. In Proceedings of the NIPS Workshop on Computational Social Science and the Wisdom of Crowds, Whistler, Canada, 10 December 2010.
77. Preotiuc-Pietro, D.; Cranshaw, J.; Yano, T. Exploring venue-based city-to-city similarity measures. In Proceedings of UrbComp 13, Chicago, IL, USA, 11–14 August 2013; ACM Publishing: Chicago, IL, USA, 2013.
78. Zadrozny, P.; Kodali, R. Analyzing foursquare check-ins. In *Big Data Analytics Using Splunk*; Apress: New York, NY, USA, 2013; pp. 231–253.

79. Richter, K.F.; Winter, S. *Landmark: GIScience for Intelligent Services*; Springer: Cham, Switzerland, 2014.