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GRAPH-BASED APPROACH FOR PERSONALIZED TRAVEL RECOMMENDATIONS

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In the evolving domain of urban mobility systems, the integration of technology with user-centric strategies is pivotal. This research stands on the foundational concept of Mobility-as-a-Service, a user-centric intelligent mobility management distribution system that seeks to prioritize human needs over mere technological infrastructure. The study delves deep into the wealth of data available through mobile sensing technologies, highlighting the unprecedented understanding it offers into human mobility patterns, thus facilitating personalized route recommendations.

The literature categorizes the study area into three interlinked categories: point-of-interest (POI) recommendation, travel planning, and trajectory modelling. In a significant stride, this research introduces a comprehensive understanding of hu-man mobility data and proposes a novel framework designed to tender personalized recommendations to travel planner users. The innovative framework employs a graph-based approach rooted in the Sussex-Huawei Locomotion dataset, leveraging an adaptation of Bellman-Ford's algorithm. This modification considers factors such as perceived fatigue, frequency of trips to specific locations, and proximity to POIs, promising a path routed in past user experiences and preferences.

Keywords: Mobility-as-a-Service, Human Mobility Patterns, Route Recommendation, Bellman-Ford's algorithm, Shortest Path

1. Introduction

Urban mobility systems need to adapt rapidly to become more environmentally sustainable, more resilient, and adaptable. They should be cantered on the needs of human beings rather than being determined primarily by their technological infrastructure. The concept of Mobility-as-a-Service (MaaS) is a user-centric, intelligent mobility management distribution system, in which an integrator brings MaaS is based on a user-centric scheme, providing on-demand tailored solutions according to individuals' needs, preferences, and expectations. MaaS application is sophisticated platform that should incorporate advanced technologies capable of analysing user data to understand their preferences and behaviours.

The proliferation of mobile sensing technologies, which include a wide range of devices such as smartphones, wearables, and Internet of Things (IoT) devices, has ushered in a new era of data availability. These technologies continuously collect a wealth of data about people's movements, interactions, and behaviours, resulting in a massive influx of data. However, while this abundance of data has enormous potential for improving our understanding of human mobility patterns.

In such context, personalised route recommendation has gained a lot of popularity as it aims by customizing travel routes to meet individuals' needs. This approach is based on the idea that people have distinctive mobility patterns that can be used to create personalized recommendations, making it simpler for them to navigate environments and safely benefit from their travel experiences. This area of study can be divided into three interconnected categories: point-of-interest (POI) recommendation, travel planning, and trajectory modelling.

Cheng *et al.* (2016) used matrix factorization (MF) in conjunction with geographical and social factors to improve POI recommendations in location-based social networks (LBSNs); for more effective recommendations, Ayala-Gomez *et al.* (2017) developed a geo group-recommender (GGR) that takes into account group preferences, category features, location data, and check-ins; Li *et al.* (2015) investigated a comprehensive approach to preference matrix construction by incorporating user behaviour, interest, check-ins, preference rankings, metric embedding, POI categories, and characteristics.

In order to address the problem of travel planning, Lim *et al.* (2015, 2018) invent-ed a time-based user interest metric in order to treat it as a "resource-constrained optimization problem"; on top of that, Zhang *et al.* (2017) incorporated limitations such as POI availability and uncertain travel times while also

tailoring user preferences based on their behaviour; Chen *et al.* (2015), on the other hand, creatively combined POIs and historical route data, using Monte Carlo-based methods to intricately model transitions between points of interest.

With regard to the issue of trajectory modelling, Liu *et al.* (2016) proposed a recurrent neural network (RNN) model able to predict future locations, from user's past trips; in order to decipher complex patterns within human trajectories, Gao *et al.* (2017) investigated a plethora of RNN-based models; Alahi *et al.* (2016) took ad-vantage of RNNs' potential in the field of computer vision for classifying general human movement patterns and forecast future trajectories.

However, for developing more personalized algorithms there are still several challenges that need to be addressed, such as the quality of the data including incompleteness and availability; the assumption that preferences and user constraints re-main static over time; additionally, the lack of assessment concerning the safety and security of the proposed routes.

The purpose of this research is the development of a framework that provides personalised recommendations to trip planner users including people with special needs. This framework makes use of a graph-based approach in the context of travel recommendation algorithms by exploring several measures that can be calculated from the preparation of Sussex-Huawei Locomotion dataset (Gjoreski *et al.*, 2018), and eventually suggest a path tailored on user's past trips and preferences. This novel method is based on an adaptation of the Bellman-Ford algorithm, which incorporates three key elements: the degree of perceived fatigue, the frequency of trips to specific locations, and proximity to points of interest (POIs).

The remainder of the paper is structured as follows. Section 2 describes dataset with Human Mobility Data and formulates framework of research. Then, section 3 is devoted to a description of results. Lastly, section 4 summarizes the main conclusions and potential future research directions.

2. Research Methods

2.1. Towards a Definition of Human Mobility Data

The Sussex Huawei Locomotion (SHL) dataset, which captures the human movement through a variety of contexts and environments, represents a great source of information in field of human mobility data (HMD). This dataset, produced through a partnership between Huawei and the University of Sussex, delves deeply into different forms of human mobility: locomotion, from more pedestrian activities like running and walking to more vehicular ones like biking and taking public transport. Three people were involved in the data collection process, which was reflected the real spontaneity and unpredictability of human mobility through a variety of every-day activities including long-distance travel and tasks like museum visits. To ensure a thorough capture of movement data, four *Huawei Mate 9* smartphones were strategically placed at different body locations: the hands, torso, hips, and bags. The sensors built into these smartphones capture a wide range of information, including environmental variables like pressure and ambient light as well as fundamental motion metrics like acceleration and gyroscope readings. The dataset's meticulous annotations, which describe not only the mode of movement but also environmental and situational contexts like road conditions, traffic scenarios, and even social interactions, further highlight the granularity of the data.

The heart of personalization means tailoring offerings to the unique characteristics of an individual's behaviour. In such context, the decision to concentrate solely on a single person (User 1) is critical. With such a narrow focus, the dataset becomes a thorough account of User 1's daily activities, capturing every move, turn, and pause, but most importantly, the peculiar behaviours, preferences, routines, and habits that are specific to this person. The dataset's exceptional length, 391 hours over a 7-month period, demonstrates the study's attention to capture both the intricacies and the broader patterns of User 1's mobility. While short-term datasets may provide snapshots of behaviour, this longitudinal method provides a more comprehensive picture, considering seasonal fluctuations, changing habits, and potential external influences on mobility. Furthermore, by removing the broader variability introduced by multiple users, the study allows a more in-depth analysis that is unaffected by the noise and disparities of a multi-user dataset.

The SHL dataset is organized in a hierarchical directory structure and Table 1 presents a summary of the data sources, descriptions, and attributes. The decision to use only "location" and "label" data in this research is supported by next considerations:

• Direct relevance: when examining an individual's mobility and behaviours, the raw geographical locations they visit (given by <position>_Location.txt) and the activity labels associated with those locations (from Label.txt) provide the most direct and unambiguous information. These datasets are

purpose-built to capture the 'where' and 'what' of user behaviours, offering a clear narrative of movement patterns and associated activities;

• Data redundancy: although rich, other data sources such as <position>_Motion.txt and <position>_API.txt provide information that can be de-rived indirectly from the location and label data. For example, the descriptor “running” implies motion. Furthermore, when we have correct labels characterising actions, Google's recognition API data can sometimes be redundant;

• Noise reduction: data sources such as <position>_Wifi.txt or <position>_Battery.txt may introduce unnecessary variables that aren't always directly or meaningfully related to human motion. By removing these, we reduce potential noise and guarantee that the datasets are most relevant to our research objectives;

• Data interpretability: location and label data are intrinsically interpretable. Latitude, longitude, and altitude give direct geographical insights, and labels translate these movements into human-understandable activities;

• Scalability: as experiments grow, the amount of data collected might become overwhelming. The study remains scalable by restricting the datasets to location and labels and ensuring that the same approaches can be utilised even as the data amount expands. Consequently, results remain consistent and generalizable across larger datasets or diverse user groups.

Table 1. Comprehensive overview of SHL Dataset

Data Source	Description	Attributes
<position>_Motion.txt	Motion and pressure data	Time, Acceleration (X, Y, Z), Gyroscope (X, Y, Z), Magnetometer (X, Y, Z), Orientation, Gravity, Linear acceleration, Pressure, Altitude, Temperature
<position>_API.txt	Google recognition API data	Time, Still confidence, On foot confidence, Walking confidence, Running confidence, etc.
<position>_Ambient.txt	Ambient light data	Time, Lumix, Temperature
<position>_Battery.txt	Battery data	Time, Battery level, Temperature
<position>_GPS.txt	GPS data	Time, Satellite data (ID, SNR, Azimuth, Elevation)
<position>_Wifi.txt	Wifi data	Time, BSSID, SSID, RSSI, Frequency, Capabilities
<position>_Cells.txt	Cell data	Time, Network type, cid, lac, dBm, MCC, MNS
<position>_DeprCells.txt	Cell data from the deprecated Android API	Time, Network type, cid, lac, dBm, MCC, MNS
<position>_Location.txt	Location data indicating latitude/longitude	Time, Accuracy, Latitude, Longitude, Altitude
Label.txt	Label tracks (Coarse, Fine, Road etc.)	Time, Coarse label, Fine label, Road label, Traffic label, Tunnels label, Social label, Food label
labels_track_main.txt	The fine label track	Label start time, Label end time, Activity label
labels_track_road.txt	The road label track	Label start time, Label end time, Label (City, Motorway, etc.)
labels_track_traffic.txt	The traffic label track	Label start time, Label end time, Label (Heavy traffic or not)
labels_track_food.txt	The food label track	Label start time, Label end time, Label (Eating, Drinking, Both)

2.2. Framework Formulation

HMD offers valuable insights into human behaviour and activities. Understanding mobility patterns is crucial for various applications, including urban planning, healthcare, and personalized services.

Firstly, data preparation is a fundamental aspect of proficient data mining, as it entails the critical task of guaranteeing the integrity and consistency of the available data. The initial task for the SHL dataset is the amalgamation of discrete datasets, namely the location data and activity labels. The process of

integration is a procedure, which involves the utilisation of *dataframe* object in Python programming language, created through *Pandas* library. The presence of minor discrepancies in timestamps can result in data misalignment, thus necessitating the utilisation of accurate time-series interpolation methods to synchronise these data points. Another crucial aspect of data preparation involves addressing the unavoidable occurrence of missing values. Various strategies are employed, encompassing basic imputations such as mean and median substitutes. The objective of these methods is twofold: to address missing values and to preserve the integrity and intrinsic patterns of the data without any tampering.

This section delves into techniques for analysing mobility data based on graph techniques that enable us to delve deeper in the concept of personalisation. In our approach we model timestamps, coordinates and activity labels as a *directed graph*, G where each *node* represents a unique *(location, timestamp)* pair, and each directed *edge* captures the transition between two consecutive nodes.

Mathematically speaking, let $G = (V, E)$ be the graph, where V is the set of nodes and E is the set of edges. Each node $v \in V$ has attributes for latitude, longitude and timestamp, represented as $v = \{lat, lon, t\}$. Similarly, each edge $e \in E$ has attributes for the type of activity (e.g., *"Walking_Outside"*, *"Bike"*, etc) and the duration it took to transition from node v_i to another v_j. In other terms, $e_{i \to j} = \{activity_label, duration\}$.

The graph is constructed by iterating through the sorted mobility data. For each pair of consecutive data points (p_i, p_{i+1}); then we create an edge $e_{i \to i+1}$ between nodes v_i and v_{i+1}. The activity attribute of the edge is set to the activity label of p_{i+1}, and the duration d is expressed as the difference $d = t_{i+1} - t_i$, where t_{i+1} and t_i are the timestamps of p_{i+1} and p_i, respectively (Figure 1).

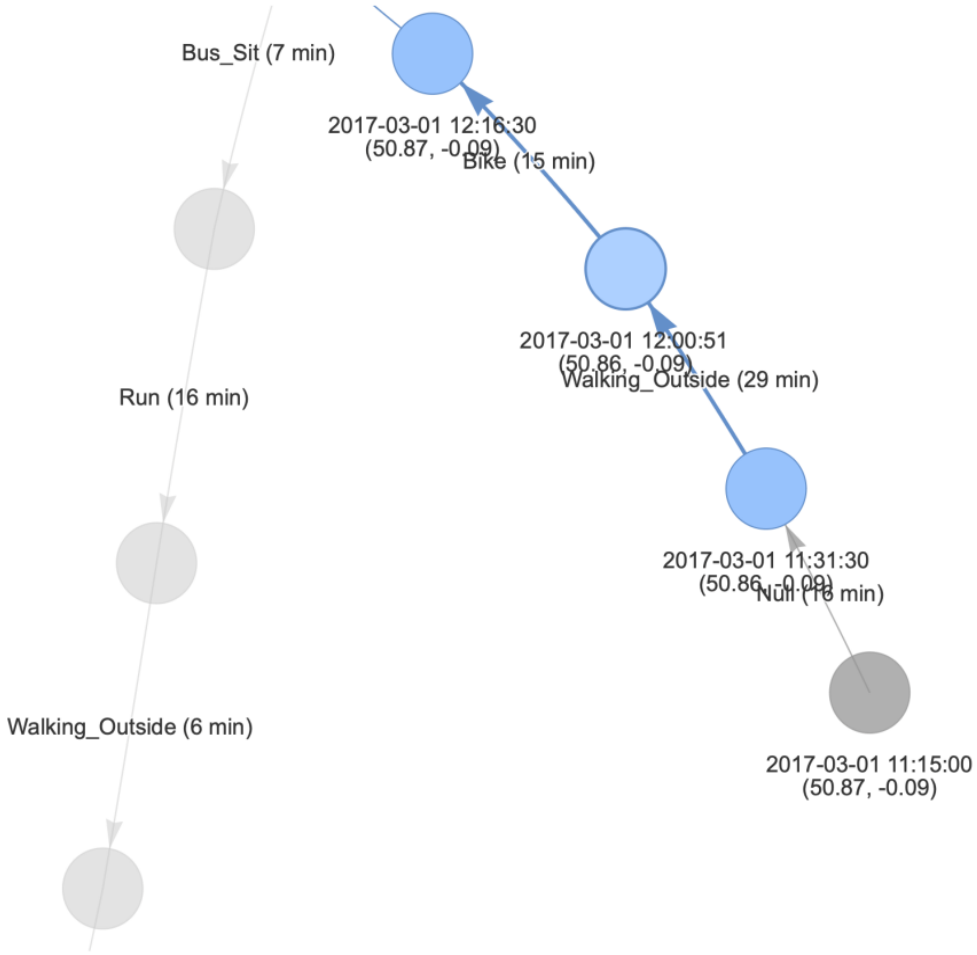


Figure 1. Graph "trip-leg" representation of User 1's activities during the first day of recording, from 11:31 until 12:16. (*Image created in Python environment, after data pre-processing*)

Subsequently, the graph obtained from the Sussex Huawei Locomotion dataset is projected onto the OpenStreetMap (OSM) road network (Figure 2). The road network graph constructed utilising the OSMnx (Boeing, 2017) library, functions as a fundamental structure that depicts the geometric configuration of roads, paths, and nodes (which are intersections or endpoints). The crucial objective is to synchronise the empirical user data (SHL Dataset) with the real network infrastructure of the city. This is accomplished by using the *get_nearest_node*() function on the previously constructed graph. By "projeting" visited locations to the nearest points on the road network, this function determines the closest node within the graph for each pair of latitude and longitude provided by the user. This *mapping* guarantees the precise integration of user data within the spatial limitations of the pre-existing road infrastructure.

This practice offers a unique way to calculate individual mobility measures that capture both spatial and temporal aspects of data. Table 2 presents measures we can calculate using the network topology. The incorporation of graph-based measures (as centrality and community detection) provides invaluable insights into individual mobility patterns.

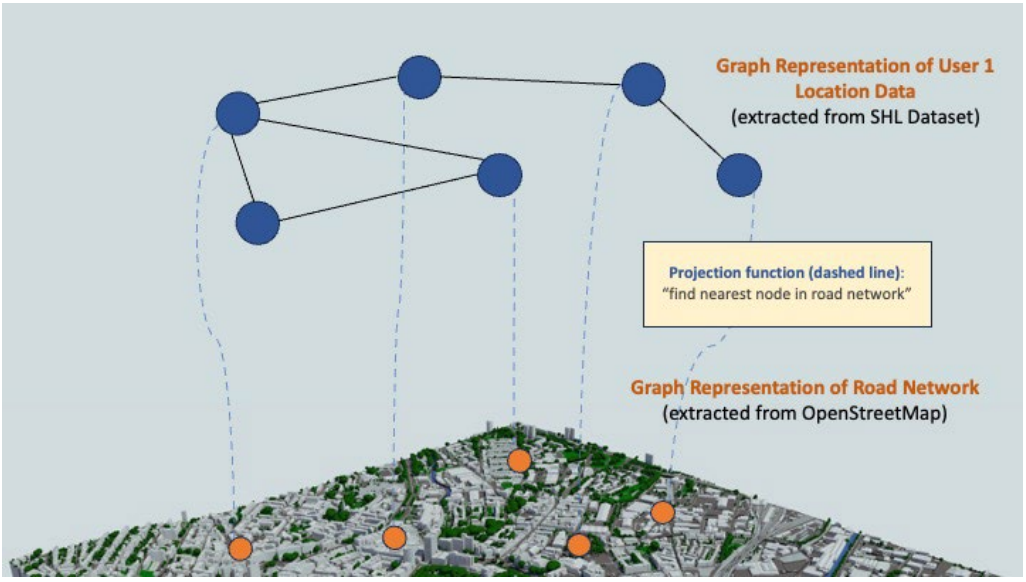


Figure 2. Projection of SHL Graph onto real Road Network graph

Table 2. Graph-based measures useful for Personalisation

Measure	Description	Potential Use Case	Reference
Degree Centrality	Quantifies the number of edges connected to a particular node	Identify activity hubs or possible points of interest	Freeman, 1978
Closeness Centrality	Measures how close a node is to all other nodes in the graph	Indicate central locations in an individual's daily routine.	Sabidussi, 1966
Shortest Path	Identifies the shortest path between nodes	Reveal routes for personalized route recommendations	Zahn, 1997
Betweenness Centrality	Measures the number of shortest paths that pass through a node	Identify key junction points for location-based suggestions	Freeman, 1977
Eigenvector Centrality	Measures a node's influence based on the quality of its connections	Distinguish between regular stopovers and meaningful destinations	Bonacich, 2007
Community Detection	Identifies clusters of nodes that are more densely connected	Contextualize types of activities or preferences for more targeted recommendations	Girvan & Newman, 2002

Degree centrality (Figure 3), for example, allow to identify key locations that a person frequently visits, making these locations ideal candidates for personalised services or recommendations. Closeness and betweenness centrality can reveal how centrally located these spots are in the person's daily routes, which is critical information for timing-specific recommendations such as traffic updates or time-sensitive

offers. Community detection adds another layer of granularity by revealing clusters of locations that are frequently visited together, possibly indicating different social circles, work-related activities, or leisure pursuits. Understanding these clusters allows services to provide more context-aware recommendations, such as a new restaurant near a frequently visited park or sending a weather update tailored to an ensemble of loca-tions where someone is likely to be. Furthermore, edge attributes such as "activity" and "duration" provide a finer understanding of the nature of movements between locations, which can be critical for recommending nearby POIs.

In the pursuit of achieving the goal to tailor personalised suggestions for individuals, a multifaceted approach to travel recommendation becomes essential. Therefore, in this paper we solely concentrate on "shortest path". Traditional shortest path algorithms focus solely on minimizing distance or time; however, this often falls short of addressing the nuanced needs and constraints that individuals might have. To rectify this, we propose a variation of Bellman-Ford algorithm (extension of Dijkstra's algorithm that allows to deal with negative weights) that incorporates three key parameters: perceived fatigue levels, frequency of visits to specific locations, and proximity to points of interest (POIs).

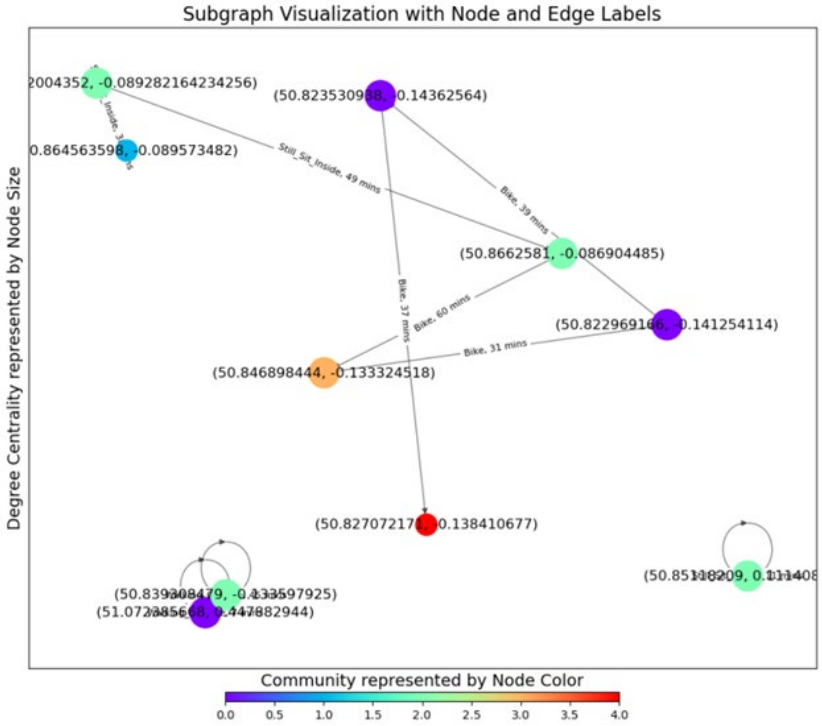


Figure 3. Example of Community Detection and Degree Centrality measures applied to SHL data.
(For better legibility, timestamps have been hidden and a subgraph has been selected)

In graph theory, the shortest path between two nodes is the path with the minimum sum of edge weights. In other words, the problem can be represented as finding the path P that minimizes:

$$Cost(P) = \sum_{(u,v)\in P} w(u,v), \tag{1}$$

where $w(u,v)$ is the weight of the edge between nodes u and v.

The "perceived fatigue level" parameter $F(u,v) \in \{1,2,3,4,5\}$, which ranges from 1 (low fatigue) to 5 (high fatigue), considers the physical or mental exertion involved in moving from one location to another. This is particularly crucial for individuals who may have mobility challenges or health conditions that make certain routes less accessible or more exhausting than others. For example, a route that includes steep inclines may be inadvisable for someone with cardiovascular issues, regardless of how short the path might be.

The "most-visited locations" parameter $V(u)$ is the number of times a node u is visited for a specific activity. It leverages historical data to identify places that hold particular significance for the individual whether it's a healthcare facility, workplace, or a leisure spot. These high-frequency locations are then given

preference in the path computation, as routes incorporating them are likely to be more aligned with the user's habitual needs and preferences.

Lastly, the "nearby points of interest" *H(u)* parameter, which represents the hotspots near a node u, adds a layer of contextual awareness by identifying valuable or essential services along the route, such as rest stops, medical facilities, or even parks for leisure. Such locations can be crucial for people who need to take frequent breaks or have specific medical needs.

By assimilating these parameters into a composite weight formula $w'(u,v)$, equation (2), can be written in the following way:

$$Cost(P) = \sum_{(u,v)\in P} w'(u,v) = \sum_{(u,v)\in P}[w(u,v) + \alpha\, F(u,v) - \beta V(u) - \gamma H(u)], \quad (2)$$

where α, β and γ are constants that allow to tune the importance of each factor based on user needs. Thus, the algorithm is equipped to generate routes that are not only efficient but also personalized to an individual's unique set of needs and preferences.

This results in a more holistic approach to navigation that prioritizes user well-being alongside efficiency, a feature that is especially valuable in healthcare applications, services for the elderly, and other contexts where individual constraints and preferences are paramount.

3. Results

3.1. Graph-based measures

The development of a framework uses a graph-based approach in the context of travel recommendation algorithms by exploring several graph-based measures that have calculated from the preparation of SHL dataset (Gjoreski *et al.*, 2018):

- ***Degree Centrality:*** the node with coordinates (50.8672, -0.0867) has the low-est degree centrality among the top nodes, with a value of approximately 0.00083. This suggests that this location is less connected compared to other top nodes. Nodes with coordinates (50.8646, -0.0896), (50.8647, -0.0893), (50.8663, -0.0869), and (50.8469, -0.1333) have higher degree centrality values, around 0.00165, indicating these nodes are significant hubs in User 1's network, possibly representing frequented locations or places with various activities.
- ***Closeness Centrality:*** the node (50.8672, -0.0867) has a closeness centrality value of 0, implying it is relatively isolated or positioned at the outskirts of the network. Nodes (50.8646, -0.0896) and (50.8469, -0.1333) have low closeness centrality values, suggesting that these locations are not centrally located in the individual's movement network. Interestingly, the node (50.8647, -0.0893) stands out with a considerably higher closeness centrality, around 0.0065, indicating that this point is central in the individual's daily routine, potentially a frequently visited location or a transit hub.
- ***Betweenness Centrality:*** the node (50.8672, -0.0867) has a betweenness centrality score of 0, highlighting that this location does not act as a bridge in the shortest paths between other nodes. Nodes (50.8646, -0.0896) and (50.8647, -0.0893) have betweenness centrality values around 0.00042 and 0.00084 respectively, suggesting that these nodes serve as significant junction points in the network, potentially acting as transition points for various routes.
- ***Girvan-Newman Algorithm:*** the community detection highlighted distinct clusters of densely connected nodes, unravelling different contexts or routines in the individual's life. The first community, for instance, comprises coordinates around (50.7564, 0.1381), (50.7573, 0.1310), and others, suggesting a closely-knit group of locations frequently visited together, possibly representing a specific context in the individual's daily routine, like a workplace or a residential area.

The analysis of degree centrality and closeness centrality (Fig. 4) in the individual's movement pattern can be a cornerstone in developing personalized services. Where the red nodes denote the top 5% nodes with the highest degree centrality, indicating notable hubs in the individual's network and the green nodes represent the top 5% nodes with the highest closeness centrality, depicting central points in the individual's routine. Identifying these parameters enables the creation of tailored recommendations for services such as eateries, shopping centres, or recreational spots situated in or near these hubs, enhancing the individual's daily experiences. Moreover, understanding the central nodes in one's daily paths could

lead to the development of services that offer optimized daily route recommendations, thus saving time and avoiding congested routes.

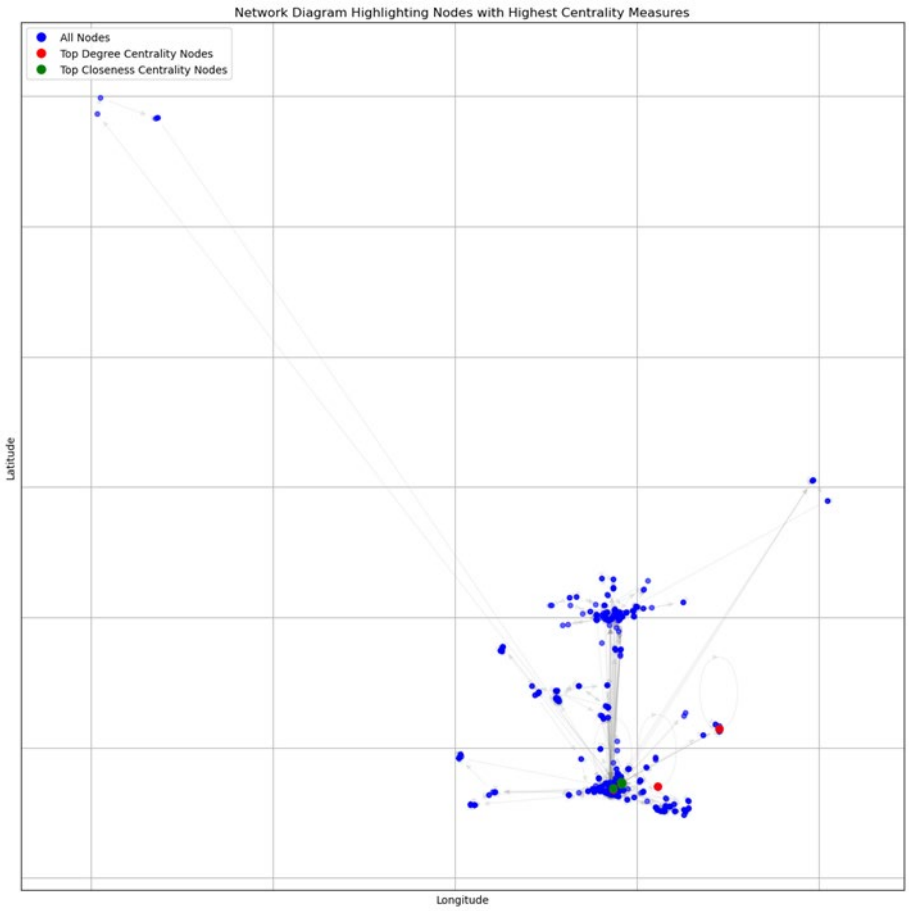


Figure 4. Graph representing SHL Dataset nodes with highest centrality

On the other hand, community detection (Figure 5) unveils intricate details about the individual's lifestyle and preferences by identifying clusters of locations that are frequently visited together. Where different colours represent distinct communities identified using the Girvan-Newman algorithm. These communities illustrate clusters of locations that are more densely connected, possibly representing different contexts or routines in the individual's daily life, helping in contextualizing types of activities or preferences for more targeted recommendations. It might help in deducing the nature of activities performed or the social settings preferred by the individual. Additionally, discerning the central nodes in the individual's mobility network through closeness centrality can provide a comprehensive view of their routine, potentially revealing regular stopovers and favourite hangout spots. This analysis can be a gateway to understanding broader behavioural patterns, offering a lens to view the subtle nuances of an individual's lifestyle. It provides a canvas to map out the preferences and tendencies of the user, which can be an essential tool in future qualitative analyses.

3.2. Bellman-Ford's Algorithm beyond Efficiency

To test this variant of Bellman-Ford's algorithm and verify assumptions, we developed a Python application reminiscent of *Google Maps*, offering a comprehensive set of functionalities designed to provide an enhanced navigation experience. Users can input starting and ending locations either as textual addresses or geographic coordinates. The app then fetches a map and road network data within a specified radius around the starting point, identifying various amenities such as cafes, pharmacies, doctors and previously visited locations. Users can select their preferred amenities, which the system then uses to score the paths between the start and end points (Figure 6).

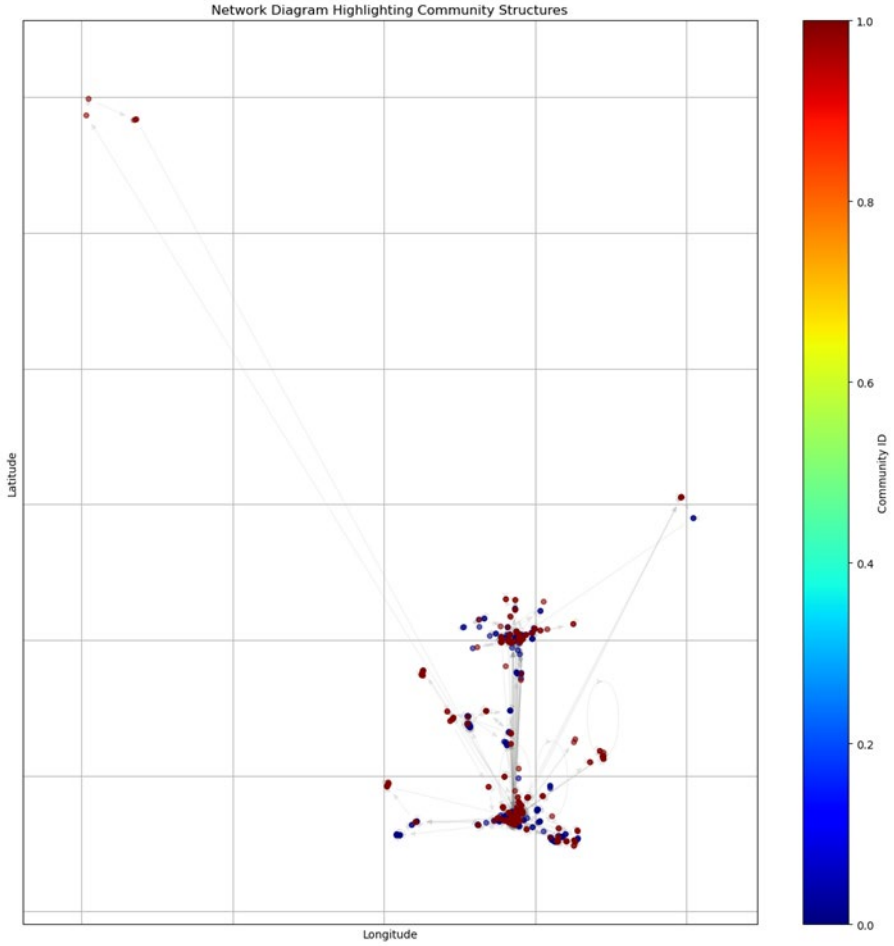


Figure 5. Graph representing SHL Dataset with most important community clusters

Through the *NetworkX* library, the app calculates the shortest path while considering both the time and distance, perceived fatigue level, nearby POIs, preferred mode of transport (e.g., walk, bike, drive) and proximity of visited locations. This is accomplished by the integration of three parameters: α, β and γ along with a user-defined fatigue level to tailor the route recommendations.

The α parameter magnifies the influence of the fatigue level on the route recommendation. This is crucial for individuals with physical disabilities or elderly users, as a higher fatigue level, paired with it' high value, would delineate a route that is least exerting, hence fostering a comfortable and safe journey.

Alternatively, the β parameter works in association with our mobility data to identify the most frequently location places to guide the user along well-known paths, encouraging a sense of comfort and familiarity. This can provide a reassuring navigation experience for those who suffer from anxiety or other mental health issues.

The γ parameter holds the potential to further enhance the route recommendation by considering proximity to specific POIs, fetched dynamically from the *OpenStreetMap* data. For individuals with special needs, a high value of γ could pave a path that goes through areas rich in amenities like pharmacies, benches, or health facilities, ensuring help is always at hand, thereby providing a sense of security during the travel.

Fig. 6 illustrates on a map both the standard (red) and custom (green) paths derived through distinct weight metrics described by equations (1) and (2), between two locations - the presumed house of User 1 and a target destination (e.g., Brighton Open Market) - and marks the most visited locations (blue dots) and potential amenities (e.g., pharmacy) with different icons. In this experiment, we set $\alpha=\beta=\gamma=0.5$ and a fatigue level $F(u,v)=3$. It is noteworthy that in our calculation the Dijkstra's algorithm, suggest the user to pass through previously visited locations and the paths often overlap between each other. This visualization can also act as a powerful tool for individuals with visual impairments or cognitive difficulties, offering a clear, color-coded, and interactive representation of the path, which can be interpreted easily and followed accurately. Finally, a notable aspect that could be implemented in future studies is the engagement of the

end-users in the route selection process, which allows individuals to define their fatigue levels and select the network type to ensure the recommendations are aligned with their current state and preferences. This participatory approach should not only improve our system, but also promote autonomy and personalization, which can be particularly empowering for persons with special needs.

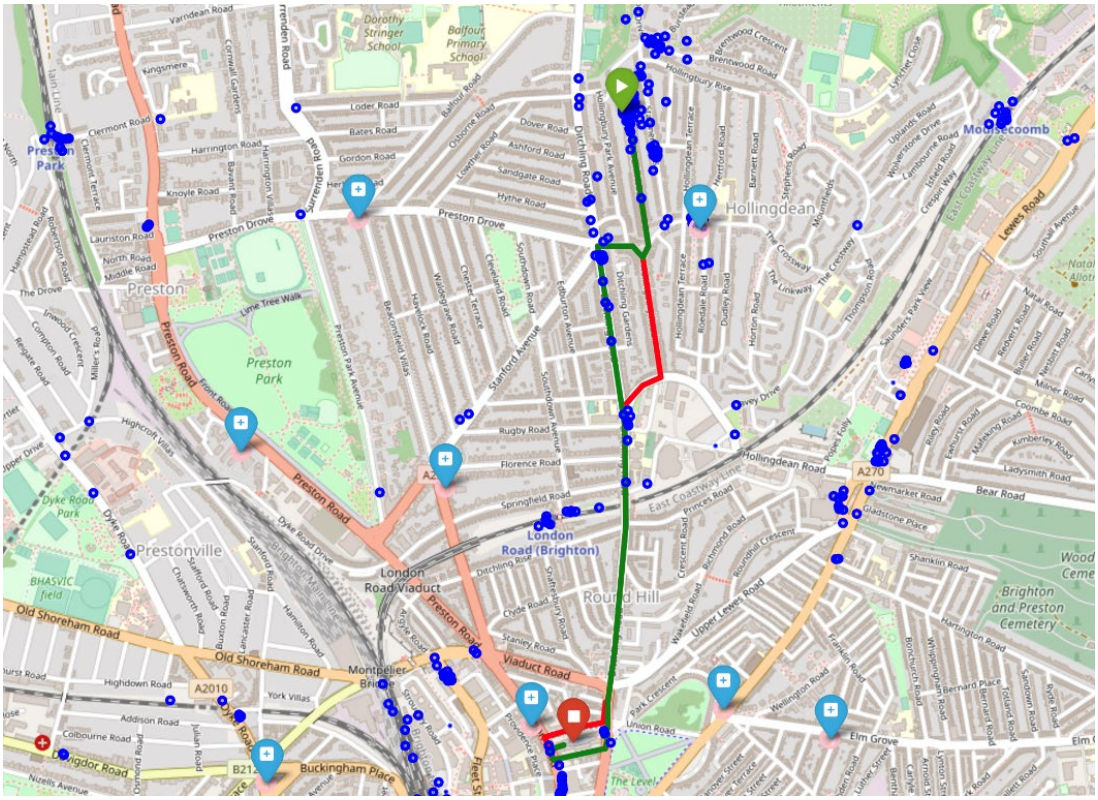


Figure 6. Calculation of shortest paths between origin and destination coordinates: standard path (in red) and path with custom weights (in green). Where, $\alpha = \beta = \gamma$ and $F(u,v) = 3$

4. Conclusions and Future Directions

The delivery of trustworthy route recommendations that are tailored to specific preferences is made possible by this dynamic synergy, effectively addressing individual needs. This paper highlights and try to cover limitations for category of POI recommendation systems, for instance, challenges in predicting preferences; recommendation accuracy is hindered by data scarcity and contextual gaps, yielding suboptimal outcomes. This research is devoted to building a model for the selection of personalized suggestions for users including people with special needs, using the concept of personalization in the field of travel recommendation algorithms. In research a variation of Bellman-Ford's that incorporates three key parameters: perceived fatigue levels, frequency of visits to specific locations and proximity to points of interest is proposed. The limitation as the basis of future improvement is include in cost function information about how safe this space for traveling.

The area for improvement could be next:

(1) the introduction of real-time traffic and environmental data to make the routing even more accurate and efficient;

(2) integration in the cost function information about safety of travelling space and dependency between fatigue level and distance;

The app could also benefit from machine learning algorithms that predict user preferences based on past interactions, thereby automating the amenity selection process. Moreover, integration with social media platforms could allow users to share their routes and favourite amenities, enhancing the community aspect of the application. User experience could be further improved by providing voice-guided directions and an option for offline access. The application could be expanded to mobile platforms for on-the-go convenience.

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