Smart Mobility Support for Vehicle-based Tourism: Theoretical and Technological Foundations

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Abstract: Vehicle-based tourism becomes more and more important in the era of the pandemic. Tourism management is an important challenge for the tourist region development. The construction of a personalized attraction visiting route for tourists with personal vehicles has a great impact on the tourist flows. The authors propose theoretical and technological foundations for smart mobility support of vehicle-based tourists. We propose to predict tourist preferences by using deep neural networks for the prediction model's implementation and demonstrated 70-80% accuracy in training on completed tourist trips to St. Petersburg, Russia. The tourist route attractiveness prediction was used to assess the constructed route quality. The attraction attractiveness and attendance prediction together with potential tourist trajectory prediction were used for attraction selection process personification. The obtained results can be used in smart mobility support systems to improve the travel experience.

1 INTRODUCTION

The tourism industry has grown rapidly in recent years and has been intensively integrated with modern information and communication technologies. Around 1.5 billion international tourist arrivals were recorded worldwide in 2019, according to reports from the World Tourism Organization (UNTWO). Before the coronavirus disease (COVID-19) outbreak restrictions applied, international travel was expected to increase by 3.3% per year between 2010 and 2030. It should be noted that the methods used by countries to combat COVID-19 such as population vaccination make perspectives on tourism growth in the nearest future. Smart tourism services usage for road travel should help to rebuild the tourist area around the world in the shortest possible time (Bulchand-Gidumal, 2022).

The fusion of information technologies and tourism has given rise to the phenomenon of smart tourism. Collection and analysis of data extracted from various sources are typical activities for smart tourism. They in combination with the use of advanced information technology make the tourist experience more enriching, efficient, and sustainable. Researches show that the use of various electronic services and tools such as recommendation services, solutions for building a route for visiting attractions can improve the overall tourist experience from travel.

More and more tourists are using smartphones during their trips that affects to attraction route formation (Kim et al., 2021). In addition, the role of vehicle-based tourism is also increasing (Cohen and Hopkins, 2019). The amount of user-generated content generated during journeys is increasing from year to year. Scientists use Big Data methods and techniques to process large amounts of information, that can be set as the basis for a predicting tourist behaviour model (Zhu and Shang, 2021). These models can be used to improve the overall performance of various e-tourism services.

The paper presented theoretical and technological foundations for smart mobility support of vehicle-based tourists that includes the route configuration process for vehicle-based tourism with personalized attraction selection and fast path construction between selected points of interest (POI). The main

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idea is to form attraction set and then propose to the tourist an effective attraction visiting plan. We use the tourist preferences prediction models for improving the tourist route quality by considering both context and historical information. The prediction models are based on the neural network and open-source data usage for tourist behaviour patterns extraction. We propose to use Kohonen self-organizing maps, EM-algorithm (Expectation Maximization), and deep neural networks.

The paper is structured as follows. The Section 2 presents related work on the topic of tourist routes construction. Section 3 describes the proposed approach to individual route configurations based on context, historical data, and tourist preferences. Section 4 describes the presented approach implementation and evaluation. Section 5 provides a paper summary.

2 RELATED WORK

(Chen et al., 2020) presents the DCC-PersIRE method, which determines the interests of the user and recommends an individual route based on them. To extract meta-information from text descriptions of places of interest the authors suggest using deep machine learning models with unsupervised learning. The route is built based on an iterative local search.

(Malik and Kim, 2019) propose a method for generating the optimal tourist route. Algorithms used in the proposed methodology are neural networks for prediction and particle as well as swarm optimization to find the optimal route. The authors develop an objective function for route optimization based on five route parameters: distance, traffic congestion, weather conditions, route popularity, and user preferences.

(Tsai et al., 2019) offers a way to recommend POI based on the photo analysis from social networks. The obtained GEO information is clustered into various categories using the topic modelling approach of latent Dirichlet distribution. Based on the obtained clusters tours are generated using the LSTM network.

(Zheng and Liao, 2019) consider the problem of tourist route configuration among groups of heterogeneous tourists using the Pareto optimality criterion. To solve this problem they proposed to use the ant colony algorithm for routing among attractions and a differential evolution algorithm for generating sets of attractions.

(Mukhina et al., 2018) uses various social networks to form an assessment of the attractiveness of a place and also uses knowledge of the region's popular types of attractions as context when building a route and performs simulation events when managing the route configuration.

(Taylor et al., 2018) uses linear programming algorithms to calculate a set of attractions recommended for a tourist to visit. The algorithm presented by the authors selects attractions located near the hotels where tourists stay.

(Hti and Desarkar, 2018) use the location taken from social networks to generate recommendations for visiting attractions. Social networks act as a source of information about visited places and reactions to them. Attractions are subjected to two-level filtering. The distance between the remaining routes is built using the Floyd-Warshall algorithm.

(Bartie et al., 2018) describes the SpaceBook project that implements an idea of a virtual guide driven by tourists based on voice analysis. The guide can notify a tourist of nearby points of interest on an interactive map. Attraction information is collected from open sources such as OpenStreetMap and social networks.

(Santos et al., 2017) presented a hybrid recommendation system that builds a tourist route based on user profiles with disabilities. The paper proposes to use an ontological approach to modelling knowledge in the tourism topic. Recommendations are based on attractions categories, the potential emotional involvement of tourists, and accessibility and amenities for travellers with disabilities.

(Chen and Tsai, 2017) describes the development of a personalized and location-based mobile travel application. The application is based on the iBike system in Taichung City, Taiwan and uses a hybrid filtering technique to collect travel information. The developed system adapts the ant colony algorithm for its work to fine-tune geolocation recommendations to tourists. Authors used a technology adoption model to interpret the adoption of information technology by users. It includes three evaluation criteria: perceived ease of use, perceived usefulness, and use of behavioural intent. The information systems success evaluation model contains six factors: system quality, information quality, system usage, user satisfaction, individual user impact, and organizational impact. These factors are related to the evaluation of the success of the information system.

(Colomo-Palacios et al., 2017) described the POST-VIA 360 platform designed to analyze the full life cycle of tourist loyalty after the first visit to the region. Based on the carried out analysis the platform can offer recommendations for visiting new places based on tourist location and artificial immunity principles.

(Kotiloglu et al., 2017) suggests a “Filtering then generating a tour” approach for creating personalized recommendations on tourist routes based on information from social networks and other online data sources. The authors proposed to apply collaborative filtering to define a subset of additional points of interest that maximize the user’s potential satisfaction with the route while the itinerary must select mandatory places that tourists must visit. The main orientation problem is solved using the iterative search for prohibitions algorithm, which must create travel itineraries. These itineraries contain all the required places and maximize the overall tourist satisfaction when using additional daily visited places, taking into account access times, opening hours, restrictions on the tourist time, his/her budget, etc.

(Cenamor et al., 2017) presented the PlanTour system, which creates personalized tourist routes using human-generated information collected from the travel social network MINUBE. The system follows an automated planning approach to create a multi-day plan with the most interesting sights of the visited region. In particular, the system collects information about users and points of interest from MINUBE and groups these points using clustering methods to divide the problem into subtasks. Then the tourist uses a destination-independent automated planner that finds quality travel plans. According to the authors of the paper, unlike other tourist recommendation systems, the PlanTour planner can organize relevant points of interest based on the user’s expected trips and user ratings from a real social network.

(Nilashi et al., 2017) authors propose a prototype of a travel advisory system that offers a method based on multicriteria collaborative filtering. This method improves the prediction accuracy of tourism recommendation systems by using clustering, sample size reduction, and forecasting methods. The authors used an adaptive network based on a fuzzy inference system and support vector machines for predictions. Principal component analysis was used to reduce the dimensionality of the samples, Kohonen self-organizing maps and EM-algorithm (Expectation Maximization) were chosen as well-known clustering methods. To improve the accuracy of recommendations of multicriteria collaborative filtering, the cluster ensemble approach, Hypergraph Partitioning Algorithm (HGPA) have been applied to SOM and EM clustering results. The authors evaluated the accuracy of the recommendation method on the TripAdvisor dataset and their experiments indicate that cluster ensembles are more predictive than single-criteria clustering techniques.

(Gavalas et al., 2017) presented a mobile travel guide, which can correctly process points of interest in their original form when generating routes without converting the geometry to a point. The routes created by the guide include extensive walking areas. Route building is based on local search with iterations. User preferences and the total time to complete the entire tour are taken as contextual information.

Based on the analysis of modern routes configuration models we proposed to divide the configuration management task into two main subtasks: formation of a set of attractions and the creation of a visiting sequence for a set of attractions. Existing approaches actively use technologies for building recommendations, to form sets of attractions, and actively personalize the route based on the restrictions imposed by the tourist. However, the considered works do not fully work with the context, and also do not use the historical data of tourists and the region when building routes.

3 THEORETICAL AND TECHNOLOGICAL FOUNDATIONS

We proposed theoretical and technological foundations for smart mobility support of vehicle-based tourists. For the tourist support we propose to form attraction set and based on this set make the visiting plan for the tourist based on his/her preferences as well as context situation in the region (see Figure 1) In the Section we consider the route configuration, tourist preferences prediction, attraction set formation as well as attraction visiting plan creation. The considered tasks allows to support of the smart mobility support of the vehicle based tourist by proposing to him/her efficient attraction attending plan taking into account his/her preferences and current situation in the region.

3.1 Route Configuration

The route configuration process within tourist region T consists of two part: attraction set formation $A_{seq}(Tr, C_{a_t}, C_{tr_t}) = \{(A_1, S_1), (A_2, S_2), \ldots, (A_n, S_n)\}$ and attractions visiting sequence creation $R(A_{seq}, Tr, C_{t_t}, C_{tr_t}, C_{a_t})$, where Tr — tourist information, A_i — region attraction, S_i — personalized attraction score for tourist, C_{t_t} — tourist region context, C_{tr_t} — tourist context and C_{a_t} — region attractions context. The route quality is measured by Equation 1, where f_{dist} — route distance rating,

f_{time} — route time rating, f_{pred} — route attractiveness rating, f_{bud} — tourist spending rating and $\alpha, \beta, \gamma, \zeta$ — correction coefficients.

$$f_{score} = \alpha f_{dist}(R, C_{t_t}) + \beta f_{time}(R, C_{t_t}) \\ + \gamma f_{pred}(R, Tr, C_{t_t}) + \zeta f_{bud}(R, C_{a_t}, C_{tr_t}) \tag{1}$$

Route distance and time rating functions compares (Equation 2) route characteristics (D_r, T_r — route distance and time) with "ideal" route (R_{min}, $D_{r_{min}}, T_{r_{min}}$ — minimal distance and time), which which is built without taking into region context. The Route attractiveness rating function (Equation 3, Sc — tourist subjective route score, $[Sc_{min} = 1, Sc_{max} = 5]$ — route estimate limits) offers an assessment of how much the tourist will like the proposed route and tourist spending rating function (Equation 3, $budget_{Tr}$ — planned tourist budget, B_{cur} — route costs, bud_{A_i} — attraction entry fee) checks if the tourist has exceeded the planned spending.

$$\begin{gathered} f_{dist}(R, C_{t_t}) = \begin{cases} \frac{D_{r_{min}}}{D_r}, & D_r > D_{r_{min}} \\ 1, & D_r \leq D_{r_{min}} \end{cases} \\ D_r \in R, D_{r_{min}} \in C_{t_t} \\ f_{time}(R, C_{t_t}) = \begin{cases} \frac{T_{r_{min}}}{T_r}, & T_r > T_{r_{min}} \\ 1, & T_r \leq T_{r_{min}} \end{cases} \\ T_r \in R, T_{r_{min}} \in C_{t_t} \end{gathered} \tag{2}$$

$$\begin{gathered} f_{pred}(R, Tr, C_{t_t}) = \begin{cases} 1, & Sc = Sc_{max}, \\ 0, & Sc = Sc_{min}, \\ \frac{Sc - 1}{Sc_{max} - 1}, & otherwise \end{cases} \\ Sc \in R \\ f_{bud}((R, C_{a_t}, C_{tr_t}) = \begin{cases} 0 & budget_{Tr} < B_{cur}, \\ 0.5 & budget_{Tr} = B_{cur}, \\ 1, & budget_{Tr} > B_{cur} \end{cases} \\ B_{cur} = \sum_{i=m}^{1} bud_{A_i} \end{gathered} \tag{3}$$

The following restrictions is taken into consideration in route construction process: $T_r \leq T_{des}, Budget_{Tr} \geq B_{cur}, A_m, \ldots, A_r \in A_{seq}, A_f, \ldots, A_l \notin A_{seq}, \alpha + \beta + \gamma + \zeta = 1$. The main goal of the proposed approach is to increase tourist satisfaction by maximizing f_{score}.

3.2 Tourist Preference Prediction

Figure 2 presents route configuration management scheme and highlights tourist activity managing tasks. We propose to track the movement of tourists based on GPS, extract data on reviews, and ratings of attractions, as well as indirectly receive information about the attractions visiting by using a smartphone. Based on data sources the following tasks were identified: identifying tourists behaviour groups based on preferences similarity, assessing tourists satisfaction after passing the formed routes, assessing changes in tourist flows and identifying typical routes among tourists.

3.3 Attraction Set Formation

Attraction set formation scheme is presented in Figure 3. Recommendation system based on synthetic coordinates *Srcs* (Papadakis et al., 2017) takes the tourists and experts attraction scores as input and predicts the personalized non-visited attraction ratings A_{scored} for the specific tourist. The recommendation creation is based on the Vivaldi algorithm (Moravek et al., 2011), which simulates a network of physical springs, placing imaginary springs between pairs of network nodes such as tourists and attractions. The used algorithm is not parameterized, does not require fine-tuning and is more resistant to the "cold start" problem.

At the same time, an attraction attractiveness prediction model ANN_{clust} is applied to change tourist attraction ratings. These models take as input the aggregated information about tourist actions and performed routes for a certain period and determine the tourist cluster, which represents as "behavioural" group. For each cluster, the most popular and high rated visited attractions were gathered and their ratings were increased by 0.2 to increase the probability of further selection by *Srcs*.

After A_{scored} acquiring the personalized attraction list is filtered by the following metrics: removal of undesirable for visiting places, allocated by the tourist himself *Rt* and removal previously visited places which have been recommended by approach $S_{A_{vis}}$. Then two tourist preferences prediction models are used to reflect the region historical data. The potential route prediction model ANN_{pred_traj} reconstructs the most popular route among the tourists by analyzing previous trips trajectories. Based on the obtained route the model retrieves the most popular POI lying on the constructed path and increase their rating by 0.1. The attraction attendance prediction model ANN_{pred_att} compares the predicted attraction attendance with the average attendance values provided by the region. If the difference is positive, the model reduces the attraction rating by 0.3, otherwise it increases it.

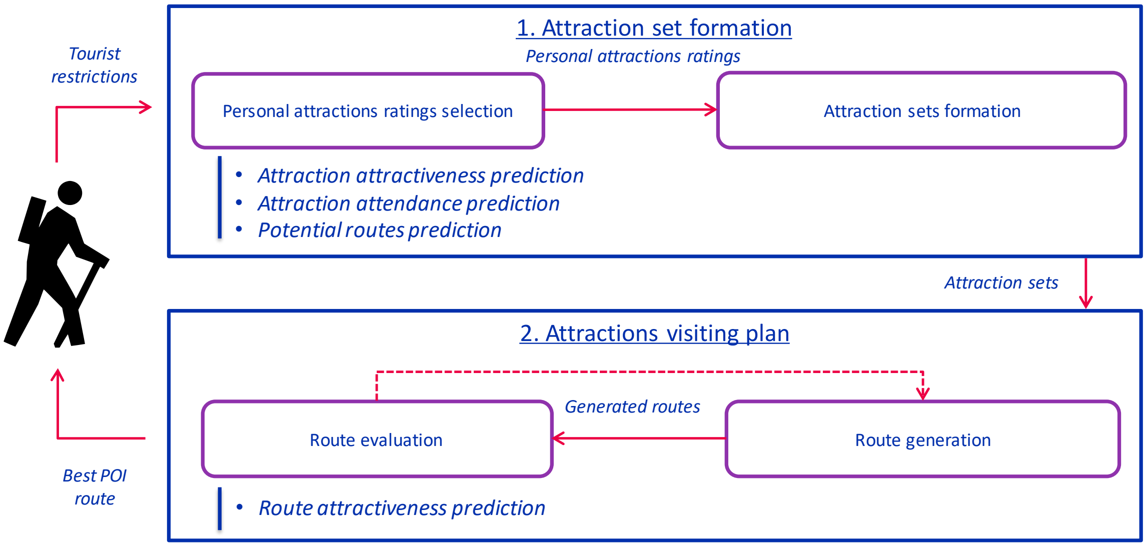

Figure 1: Smart mobility support of vehicle-based tourists.

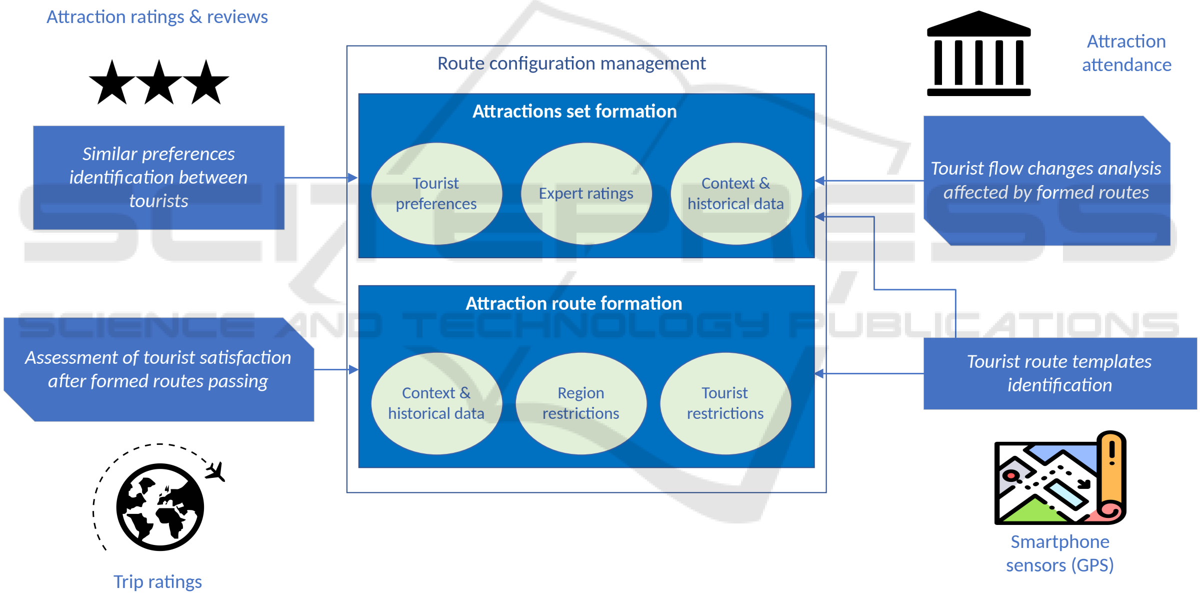

Figure 2: Route configuration management scheme.

The filtered attraction list $A_{filtered}$ is divided into the n attraction sets $A_{seq_i},\ldots,A_{seq_n}$ by using the sliding windows technique with length k, which is set by tourist restrictions Rt. The tourist starting and finishing points are inserted into each attraction set. All constructed sets are validated on the simplified region graph, where the vertex is a regional attraction and the edge is a minimal distance between two POI. The validation consists of potential route duration comparison with the desired duration given by tourist and attraction working hours check. If the number of validated sets is less than m, the cycle of attraction sets creation and validation continues. In the end the approach returns the personalized and validated attraction sets $A_{seq_i},\ldots,A_{seq_m}$.

3.4 Attractions Visiting Plan

Figure 4 describes attractions visiting plan creation process. At first the full region graph G is constructed, based on the information from Openstreetmap[1]. In addition, the road traffic information is gathered from the smart city services and applied to G for creating

[1] https://www.openstreetmap.org

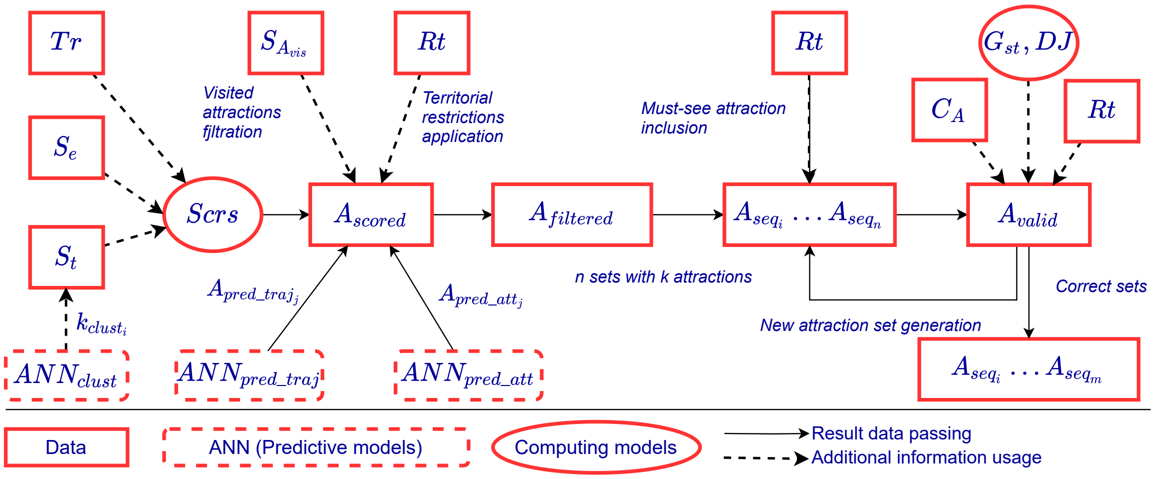

Figure 3: Attraction Set Formation.

a graph G_{mod} with current region state information. Next, the following steps are cyclically performed.

- The m attraction sets are taken as input for sequence creations. attractions inside the sets are sorted by proximity to the tourist.
- For each set the route R_i is created by using the multilevel Djikstra algorithm (Delling et al., 2017). This modification of Djikstra algorithm allows to quickly build routes for the proposed places due to the internal representation of the graph in the form of nested cells.
- For each constructed route R_i the quality rating R_{score_i} is computed by using the f_{score}. The f_{score} uses 0.25 as a default value for $\alpha, \beta, \gamma, \zeta$ correction coefficients if the tourist did not enter his preferences for the formation of routes in the mobile application, otherwise, the different distribution of weights is applied. The route attractiveness prediction model is used as part of f_{score}.
- The quality scores and route characteristics are saved in the tabu list, and the mutation process is occurred by exchanging 20% of attractions between random set pairs. If the received route was previously evaluated in the tabu list, the route is generated again.

The condition for terminating the cycle is exceeding the iteration limit (it is configured individually for each region) or exhausting the set of routes available for generation. In the end, the tourist receives the route with the maximum R_{score_i}, which represents the highest quality available route.

3.5 Tourist Preferences Prediction Models

Based on the examination of the modern studies with the analysis of tourists states and a tourist region within the framework of the predictive models use, we decided to use solutions based on a neural network approach. Neural network models have a better predictive ability for identifying non-obvious functional dependencies within the tourism system than traditional statistical analysis methods. Another advantage of such models is independence on the specific statistical characteristics of the available dataset, as well as resistance to incomplete, redundant and noisy data. It is also worth noting that neural network models show the best results for predicting the states of objects and subjects of systems when accessing a large amount of historical data that a tourist system can provide. Neural network models meet the requirements of taking into account seasonality and delays in assessing management efficiency through the use of historical data.

In Table 1 we proposed the several types of neural networks to solve different prediction tasks. We taking into account the characteristics of datasets for each forecasting task. Predicting the attractiveness of the route and attractions do not have temporary events, therefore the type of networks, based on the LSTM approach and taking into account time events are not suitable for this type of task, in contrast to the tasks of predicting the attendance of attractions and potential routes. Predicting the attractiveness of a route is solved within the framework of classification problems, for which a deep neural network can be applied. For the task of predicting the POI attractiveness, self-organizing Kohonen maps are used, which solve the problem of clustering users.

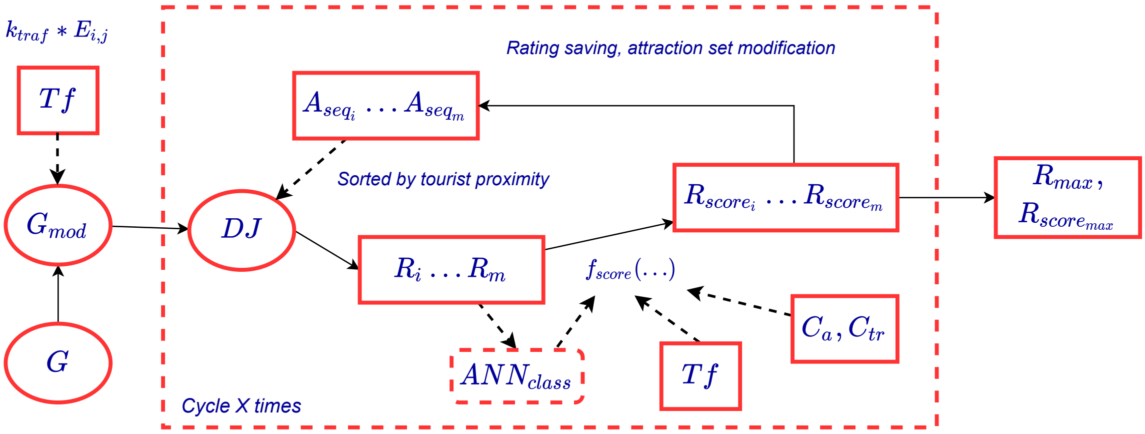

Figure 4: Attractions visiting sequence creation.

Table 1: Neural network architecture selection based on prediction task.

Task	Chosen architecture	Dataset information	Network type justification
Route attractiveness prediction	Deep neural network	Routes ratings by tourists, routes characteristics	Supervised learning, trips do not affect each other, no time events
Attraction attractiveness prediction	Self-organizing maps	Average characteristics of completed routes, tourist preferences	Unsupervised Learning, no time events
Attraction attendance prediction	Bidirectional LSTM	Time distribution of tourist attractions visitation, weather and budget costs	Supervised learning, events are distributed over time and has influence on each other, context clarifies the situation with attendance
Potential route prediction	Bidirectional LSTM	GPS trajectories of tourists	Supervised learning, events are distributed over time and influence each other, time and type of terrain set the context

The proposed neural network architecture consists of one input layer, one normalisation layer, three hidden layers with 128 neurons, and one output layer. Hidden layers used ReLU activation function.

Implementation details of tourist preferences prediction models described in the (Mikhailov and Kashevnik, 2021), (Mikhailov and Kashevnik, 2020). The overall accuracy of model prediction was 70-80% depending on the prediction type. For the route attractiveness prediction model, as a context expected distance and duration of the formed route the number of visited attractions and their average rating, current traffic assessment, current weather situation and tourist attractions preferences are used. As for attraction attractiveness prediction, the model defines the context as the attendance of the attractions of the region, the number of generated tourist content during tourist trips, the average budget spend and tourist preferences. Historical data is determined by the average duration and distance of trips, the number and rating of points of interest, and the average travel speed.

For attraction attendance prediction information about the activity of visiting attractions with a breakdown by day is used as historical data. The weather situation on a specific day and the total spending of the monetary budget is used as contextual information. The model for predicting potential routes based on the days of the week and the type of road can form potential tourist routes that can be used as an additional source of extraction of popular attractions. The neural network model uses a part of the path trajectory in the format (azimuth between points, distance between points) as historical data.

4 IMPLEMENTATION AND EVALUATION

4.1 Architecture of the Protopyte

Figure 5 describes the system prototype architecture, which implements the proposed route construction approach. The prototype uses a data-driven approach for route configuration creation and consists of different micro-services. For the functioning of services in an isolated environment, the Docker[2] was used, which allows store each of the system components in a container. This virtualization technique allows to conveniently deploy, maintain and scale a system for different tourist regions.

The system prototype architecture can be divided into three parts: collecting data about a tourist when moving in a tourist region, tourist behaviour analysis and the tourist route creation, visualization of the results of the analysis of tourist behaviour. During the travel a tourist uses his electronic device (smartphone, tablet, etc.) with a tourist support mobile application (Mikhailov and Kashevnik, 2018). This application monitors the state of sensors (GPS, magnetometer, etc.), shows the route among the attractions, offers to evaluate the route and attractions. The application also sends information about the tourist actions and statistics from sensors to the database.

The tourist information transfer is carried out over the HTTP protocol to the REST-API service. The entry point of this service is the Nginx HTTP server[3], which provides access to a backend written in the Python programming language. Due to a large amount of information coming from tourists in the tourist region, it was decided to use asynchronous framework aiohttp[4] for building a REST-API service that allows processing a large number of requests in parallel without high costs for I/O operations. Also, to ensure parallelization of requests, and Gunicorn HTTP server was used, which allows to launch and manage parallel instances of the tourist information processing service.

A Postgresql[5] database was used as the information storage. All information is stored with indexed timestamps according to the concept of a digital pattern of life (Mikhailov and Kashevnik, 2020). This enable fast information analysis about the tourist and the tourist region. Elasticsearch technology stack was used as additional storage of unstructured data — Logstash — Kibana[6], which allows to track incoming tourist information in real-time.

Tourist behaviour analysis services use deep ANNs, available information from Postgresql and Elasticsearch databases to extract the behavioural characteristics of tourists and use them to support vehicle-based tourist activity. The region information extraction service (Smirnov et al., 2020) retrieves information about attractions within a tourist region based on geo-information from the OpenStreetMap service, information from Wikipedia (multimedia information) and Google Places (attraction rating information). Deep neural network models are implemented using the Python programming language and the Tensorflow[7] library. The formation of sets of attractions uses in its work the recommending system ScoR (Papadakis et al., 2017), based on the use of synthetic coordinates. The OSMR[8] platform was used to create a sequence of attraction visitation to implement a multilevel Dijkstra algorithm.

The service for visualizing the results of the analysis of tourist behaviour was implemented using the Javascript programming language and the Vue.js library[9], which allows to implementation of a Single Page Application (SPA) approach to creating websites. The service allows to view current tourist trips in real-time, view the state of the tourist and the tourist region as well as visualize the results of predictive models.

4.2 Experiments

The approach evaluation consisted of a “blind” comparison of the expert routes and the generated routes by the described approach. Each of the proposed routes passed through the city of St. Petersburg, Russia. Experiment participants took part in a survey based on a website that displayed routes on an interactive map. The website was developed in the Javascript programming language using the Vue.js library, and the results were processed using the Python programming language.

At the survey, start participant had to enter personal information — gender, age and information about St. Petersburg residence. 63 people participated in the survey in total, 31 people were aged 18–30 years (49.2% of the total sample), 18 people — at the age of 31–45 years (28.6%), 14 people — at the age of 46–64 years (22.2%). Most of the subjects

[2] https://www.docker.com/
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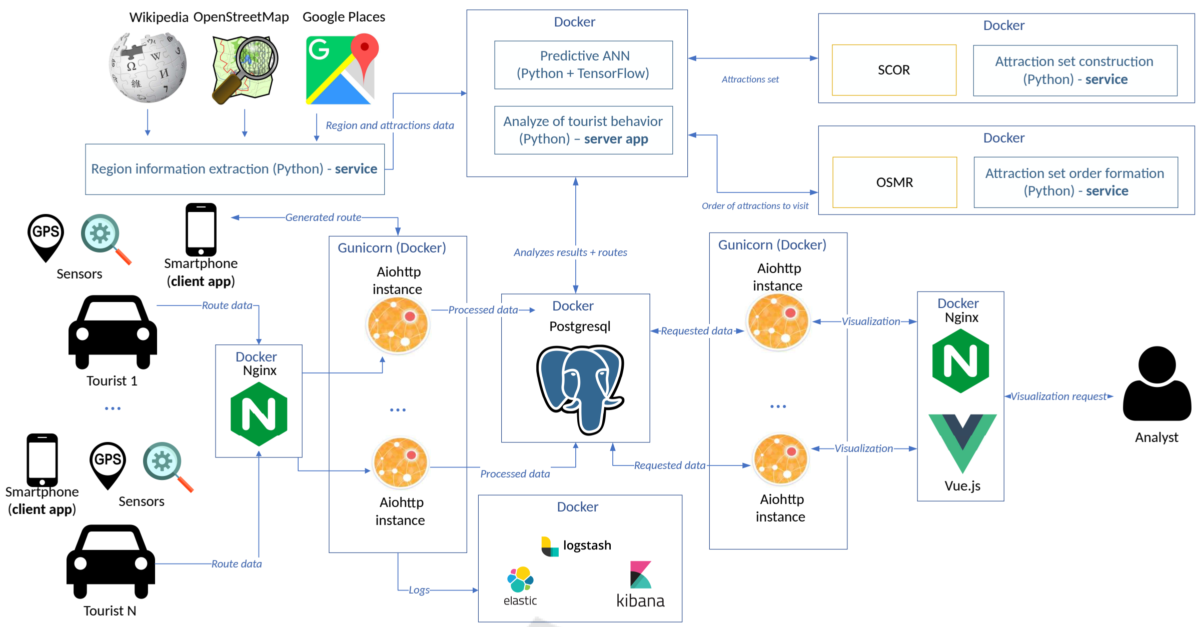

Figure 5: System prototype architecture model.

live in St. Petersburg (39 people — 61.9% of the total sample), the remaining 24 (38.1%) people lived in the Novgorod the Great, Kaliningrad and Moscow regions.

The survey participants were asked to evaluate five routes groups (Fig. 6), consisting of 3–7 entries. Route groups could be either general or thematic. The general group contains less than 50% popular region points of interest within a given attraction set. The thematic group contains more than 50% popular attractions or all route POI were subject to the same theme such as “Literature in St. Petersburg”, etc. When building routes, the approach took into account the current context and historical information about the attractions and the region. The participants were asked to rate the routes within each group on a ten-point scale, where 10 is the highest possible route quality score.

Each group contains one approach generated route, at least one expert’s route and at least one “mixed” route. The routes of GPSMyCity, Inspirock, TripAdvisor services were used as expert routes sources. The “mixed” routes has attractions set based on the expert’s route, however, the routing process between POI was done using the Multilevel Djikstra algorithm. Each route was obtained in audio guide form, which implies not direct visiting attractions and receiving multimedia information about them using a tourist smartphone.

As part of the first group of routes, the goal was to compare the routes of attractions in the centre of St. Petersburg, located near the Hermitage. As part of the second group of routes, sights associated with the Hermitage, the Peter and Paul Fortress and the Cruiser Aurora were used. The third group of routes considered the sights of the Vasileostrovsky district, but at the same time, when constructing routes, the situation was stimulated, when several popular attractions were packed. In the fourth and fifth groups, routes built in the area of Apraksin Dvor and Admiralteysky Island were compared.

For each of the routes within the groups, the arithmetic mean of all ratings was calculated (Table 2). As a result we made the following conclusions:

- Participants preferred the generated routes over experts ones in the general route groups. However, in the thematic group’s participants rated the expert’s routes higher. This is due to the general decrease in the number of popular attractions in the approach routes and the consideration of POIs attendance.
- An analysis of the participant comments showed that other cities residents (10 out of 24) more often than indigenous people (8 out of 39) noted an interesting choice of attractions in the routes created using the presented approach. Some survey participants used the routes proposed by the method and highly appreciated it in practice.

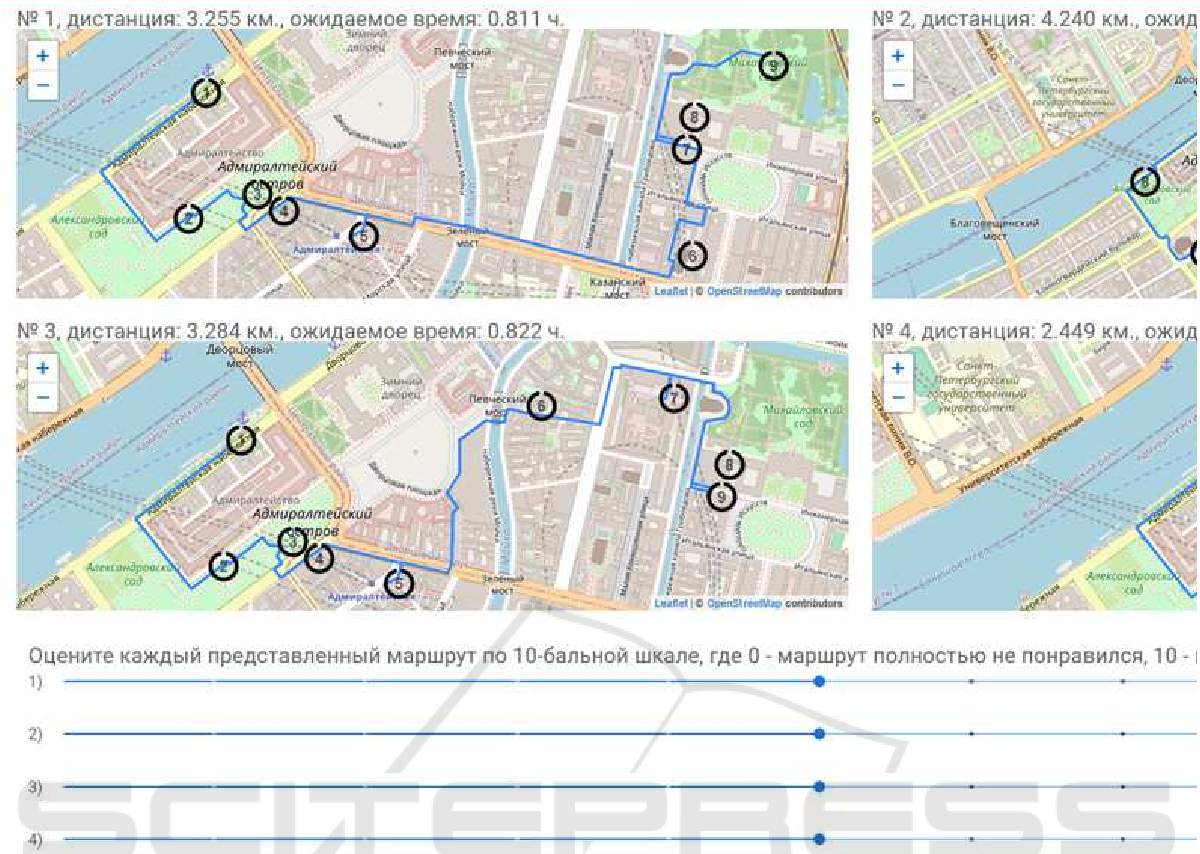

Figure 6: Survey page with interactive routes.

Table 2: Average route scores within groups.

#	Approach routes	Experts routes
1	**7.83**	7.58
2	**8.23**	6.32
3	7.12	**7.83**
4	**6.88**	5.67
5	**7.43**	6.58

5 CONCLUSIONS

The paper presented theoretical and technological foundations for a tourist smart mobility support taking into account historical data and tourist preferences. The evaluation shows that the proposed approach is effective in the tourism domain and allow to recommend relevant attractions to him/her. The implemented survey shows that the overall route scores increase to 8.5% when using the presented approach that is in contrast to the routes proposed by experts, takes into account both the context of the tourist and the tourist region and work with the accumulated historical data, which allows the personalizing route to the tourist.

The presented approach has limitations. We do not take into account time required to visit the attraction as well as opening hours. This ideas is our future work.

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