.

CHIP: a Recommender System and a Travel Planner for Cultural Tourism

Carla Binucci[1,2,†], Giulio Biondi[2,*,†], Emilio Di Giacomo[1,†], Walter Didimo[1,†], Alice Fortuni[1,†] and Giuseppe Liotta[1,2,†]

[1]Department of Engineering, University of Perugia, Perugia, Italy
[2]Joint Research Centre for the Digitalisation of Cultural and Environmental Heritage (CeDiPa), University of Perugia, Perugia, Italy

Abstract

In recent years a renewed focus has been posed on the promotion of Artificial Intelligence (AI) methods to support the definition of new means to understand, study, preserve, valorise, and enjoy the Cultural Heritage (CH). In particular, the fruition of CH by the greater public can benefit from the availability of intelligent recommender systems and travel planners. On the basis of appropriate data and meta-data associated with cultural attractions and curated by experts, such systems help tourists to plan personalised cultural trips and enjoy tailored experiences. Moreover, territorial administrations, policy makers, and other stakeholders have the opportunity to promote territory, possibly focusing on less-known material or immaterial heritage. In this paper we present CHIP (Cultural Heritage Itinerary Planner), a recommender system and travel planner for cultural tourism. We present an overview of the system architecture and then focus on the solutions implemented for the Travel Recommender System (TRS) module, which provides tourists with relevant recommendations of points of interest, and for the Travel Planner (TP) module, which builds personalised itineraries based on the users' preferences and taking into account travel constraints. CHIP is currently being tested with data about the tourist attractions of the Umbria region in Italy, a region with a strong cultural vocation. Finally, we highlight future developments and goals of the project.

Keywords

Cultural Heritage, Cultural Tourism, Recommender Systems, Travel Planners

1. Introduction and Related work

In the last decades Artificial Intelligence research, coupled with an ever-growing availability of both structured and unstructured data, led to vast developments across several domains, including Cultural Heritage (CH). The CH field, characterised by an inherent multi-disciplinary approach involving the cooperation of humanities and science experts, is experiencing an increasing interest in the application of cutting-edge technologies at all levels, and is a key target for future investments and research, as clearly demonstrated by initiatives such as ECCCH [1], aimed at building a European Cultural Heritage cloud. Relevant research tasks include the study, preservation, valorisation, and fruition of both material and immaterial heritage, with a twofold target: (i) on the one hand, researchers, practitioners, institutions, industries, and other stakeholders; (ii) on the other hand, end-users such as travellers, which benefit from the introduction of state-of-the-art technologies, such as Recommender Systems, Travel Planners, VR/AR, and digital storytelling to build new, personalised fruition paths.

3rd Workshop on Artificial Intelligence for Cultural Heritage (AI4CH 2024, https://ai4ch.di.unito.it/), co-located with the 23nd International Conference of the Italian Association for Artificial Intelligence (AIxIA 2024). 26-28 November 2024, Bolzano, Italy
*Corresponding author.
†These authors contributed equally.
‡Research supported in part by MUR PON Project RASTA, ARS01_00540.
carla.binucci@unipg.it (C. Binucci); giulio.biondi@unipg.it (G. Biondi); emilio.digiacomo@unipg.it (E. Di Giacomo); walter.didimo@unipg.it (W. Didimo); alice.fortuni@studenti.unipg.it (A. Fortuni); giuseppe.liotta@unipg.it (G. Liotta)
0000-0002-5320-9110 (C. Binucci); 0000-0002-1854-2196 (G. Biondi); 0000-0002-9794-1928 (E. Di Giacomo); 0000-0002-4379-6059 (W. Didimo); 0000-0002-2886-9694 (G. Liotta)

In this paper we present *CHIP* (*Cultural Heritage Itinerary Planner*), a new framework that combines a recommender system and a travel planner. It is a powerful tool for travellers, able to provide user-tailored Point of Interest (POI) recommendations in the context of a touristic territory (e.g., a city or a region), and to plan one or more itineraries built on the recommendation-phase results, while satisfying the travel constraints expressed by the user. CHIP is useful for tourists who want to optimize their time and to visit multiple attractions efficiently. It is being developed in the scope of RASTA[1], a broader MUR Italian project aimed at the promotion of the territory and cultural heritage through the use of advanced technologies to develop personalised user experiences.

1.1. Cultural Travel Recommender Systems

A Recommender System (RS) is a computer-based intelligent systems that exploit Big Data and Artificial Intelligence (AI) techniques to determine the appreciation of a user for an item and provide it with a list of additional items they may be interested in [2]. A well-designed RS helps end-users in product research, providing a better experience and increasing customer satisfaction. Furthermore, it enables sellers and content providers to increase sales and engagement. Designing an RS for the tourism sector is a challenging task [3]; with an ever-growing offer of cultural initiatives, and a renewed attention on the valorisation of the cultural heritage, travellers may experience difficulty in designing their trips. A Travel Recommender System (TRS) is specifically designed and developed for the tourism sector, to assist travellers in devising travel itineraries that better suit their preferences. At the same time, it allows policy-makers to gain insights, develop strategies, and promote less-known destinations. TRSs acquire information about users' preferences with respect to a set of Topics Of Interest (TOIs), i.e., macro-categories such as Culture, Religion, or Landscape, and exploit them to compute travel recommendations. TRSs then provide users with selected lists of Points Of Interest (POIs), i.e., attractions or activities which represent possible destinations to choose from, to plan personalised itineraries and increase satisfaction, smoothing the entire trip design process. Traditional techniques for TRSs have been successfully applied in the literature to the tourism sector; a broad classification of the different approaches is the following:

- *Content Based RSs*: Recommendations are provided by matching the POIs characteristics with the user preferences. Tipically, POIs are characterised by textual descriptions and features, which are thoroughly analysed, usually by means of machine learning algorithms to build POIs representations. Similarly, user profiles are built upon information provided by the users themselves, e.g., preferences towards sets of TOIs and explicit feedback/evaluation on previous recommendations. POIS that best fit the user profile are then recommended to the user [4]. Content-based approaches are particularly effective in cultural tourism recommendations [5].
- *Collaborative Filtering RSs*: In this approach, recommendations for a user are drawn from the feedback that other similar users provided; in a TRS, an applicable similarity criterion between tourists is the preference of users towards TOIs [6].
- *Hybrid RSs*: They integrate different recommendation techniques, such as content-based and collaborative filtering, to combine their output and provide users with more accurate and personalised recommendations [7].

For further details on the subject, we refer the reader to a recent broad survey about recommender systems in the tourism sector [8].

1.2. Planning Cultural Itineraries

The problem of computing itineraries given a set of destinations to cover and a starting point has been widely studied in the literature. Prominent examples are the Travelling Salesman Problem (TSP) and the Orienteering Problem (OP) [9]; variants have been proposed to account for a vast set of constraints, including capacity, time, resources, travel means, etc. Itinerary planning problems are usually NP-hard,

[1] Realtá Aumentata e Storytelling Automatizzato, Augmented Reality and Automated Storytelling - Italian MUR PON project.

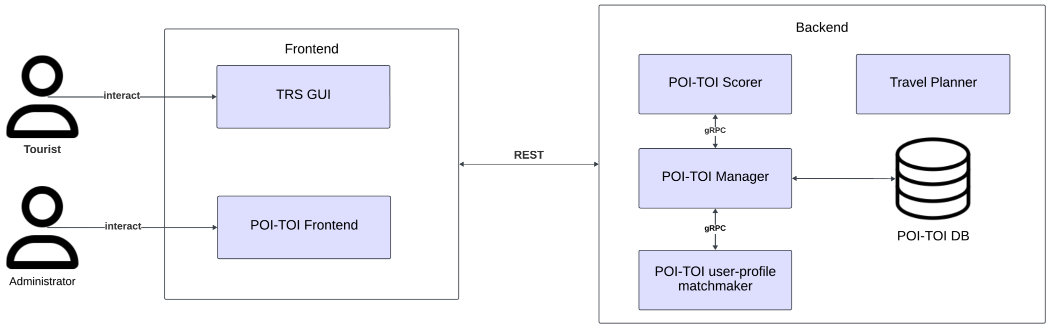

Figure 1: System architecture.

and therefore heuristics and meta-heuristics have been widely considered to speed-up the computation at the expense of optimality. The specific problem of planning cultural itineraries[10] has been dubbed Tourist Trip Design Problem (TTDP) in [11]; the goal is to compute itineraries that respect a set of constraints, while maximizing one or more objectives, such as profit for the user with respect to his/her preferences, time spent on the road, or number of visited attractions. The constraints may include budget, travel times, opening times, transport means, and POIs scores, increasing the complexity of the problem. Several approaches for the TTDP have been proposed, mainly based on Operational Research. The basic version of the problem is modeled as an OP [11]. Variants are proposed to account for additional constraints, e.g., the Team Orienteering Problem (TOP) for multi-day itineraries and the Orienteering Problem with Time Windows (OPTW) for POIs opening times. Other approaches for the TTDP are based on a related problem, the Vehicle Routing Problem (VRP), whose goal is to define strategies to serve customers efficiently with a fleet of vehicles; under this approach, each day of the trip is modeled as a different vehicle, and customers are modeled as POIs [12]. For further references, we refer the reader to a comprehensive survey on TTDP [13].

2. System Architecture

CHIP is based on a micro-services architecture, to grant scalability and modularity. Each backend module communicates with the others through gRPC, whereas the frontend modules, i.e. the GUIs for tourists and administrators, communicate with the backend modules through REST APIs. An overview of the architecture is shown in Figure 1.

A prototype version of CHIP is available at the URL https://mozart.diei.unipg.it/rasta/. It is based on data provided by Umbriatourism, the tourism office of the Umbria regional administration, which collected a total of 624 POIs, each associated with its geographic coordinates and a textual description in English language. We describe the system modules in the following paragraphs.

2.1. POI-TOI Scorer

The POI-TOI scorer backend module represents the core of the CHIP framework; it is responsible for assigning each POI a relevance score for each TOI. Informally speaking, the essence of the problem is to "estimate" the "conceptual distance" between TOIs and POIs, and then report those POIs that are "closer" to the TOIs. The question behind this problem is how to use the descriptions, and perhaps additional features of POIs and TOIs, to deduce the relevance of the different POIs with respect to the various TOIs. In the approach of [5], this question has been addressed by means of shortest paths in a conceptual network constructed by analyzing Wikipedia pages. However, this solution has several limitations: First of all, there is a lack of information on Wikipedia for many POIs that are not included in the most popular in the world; also, the conceptual network is constructed based on hyperlinks among the Wikipedia pages, which do not always reflect semantic connections; finally, unlike POIs, it is often difficult to associate a desired TOI with one or more specific Wikipedia pages.

Table 1
Ground truth-POI-TOI scorer ranking correlation values

TOI	Pearson	Pearson P-Value	SpearmanR	SpearmanR P-Value
Religion	0.6675	<0.0001	0.5515	<0.0001
Craftsmanship	0.4920	<0.0001	0.3379	0.0030
Landscape	0.2907	0.0114	0.3054	0.0077
Sports	0.2943	0.0104	0.1446	0.2157
Culture	0.0548	0.6406	0.0055	0.9626

In this paper a machine-learning based approach is adopted to build latent-space representations of POIs and TOIs starting from textual content, e.g., POIs textual descriptions and sets of words semantically related to TOIs. POIs descriptions are usually written in some natural language by travel experts; it is therefore necessary to perform simple Natural Language Processing tasks, such as tokenisation and stopwords removal, to retain semantically-rich words only that describe the POI context. Word embeddings can then be computed and subsequently aggregated to provide a single description-level embedding for each POI; common aggregation strategies include component-wise averaging or cosine centroid. Likewise, an aggregated embedding is computed for each TOI. TOIs can either be associated with a textual description, like POIs, or linked to semantically-related keywords, e.g., in an ontology. Nevertheless, the same embedding strategies can be applied. Once the embeddings are obtained, the proximity between a POI and each TOI can be determined. The cosine similarity between the POI representation and each TOI is computed. Consequently, if we consider a number of k distinct TOIs, for some positive integer k, each POI is represented by a vector $v \in \mathbb{R}^k$, where $v_i \in [0, 1], i = 1 \ldots k$. CHIP considers six TOIs, namely Landscape, Culture, Religion, Sports, Craftsmanship, and Food/Wine, which capture the specificities of the Umbria region. The word embeddings have been extracted from the *Word2Vec* [14] pre-trained *word2vec-google-news-300* model for the English language, and have then been aggregated by calculating the cosine centroid to compute POI-level and TOI-level embeddings. For TOIs, instead, the source documents consist in sets of words semantically related to the topics itselves; as an example, for the Religion TOI the following words were selected: faith, priest, jesus, spiritual, church, christ, christian, worship, sacred, rituals, religion, sanctuaries, religious, cathedral, and chapel.

To evaluate the POI-TOI scorer performance, its output has been compared to a ground truth provided by 12 experts in the cultural domain in the Umbria region. These experts have been asked to manually annotate a sample of about 12% of the 624 POIs with a relevance score for each TOI; a minimum of three annotators was employed for each POI, and the scores were averaged TOI-wise. Then, for each TOI, the rankings induced by the aggregate manual evaluation have been compared to those of the POI-TOI scorer output. In our experiment, we did not include the Food/Wine TOI, as it was difficult for the domain experts to clearly classify POIs that were particularly relevant for this category. From the resulting data, we observed medium to high correlation levels for the Religion, Landscape, and Craftsmanship TOIs. On the other hand, the results for Sports and Culture suggest the importance of further refinements of our techniques for these TOIs (see Table 1).

2.2. User-Profile Matchmaker

The User-Profile Matchmaker backend module ranks the POIs for a user according to the user preferences and the POI-TOI relevance scores computed by the POI-TOI Scorer module (see Section 2.1). In a Travel Recommender System one of the main challenges is to tailor the POI recommendations to the user preferences, which may be highly specific in terms of preferred activities/events or cultural attractions; thus, after modeling user profiles and POIs, adequate techniques are needed to accurately match them and provide custom recommendations.

When new users access CHIP, they are asked to express their preferences for each TOI, on a scale from 1 to 10; the user is then associated with a preference vector $p \in \mathbb{R}^6$, where each component p_i specifies the appreciation towards TOI i, in the same order as the POI-TOI proximity vector v. To assess the correlation between each POI and the user's preferences, a similarity measure is computed between the preference vector p and the POI relevance vector v; the similarity values are then used to induce a POI ranking, in which the top-placed POIs are considered more adherent to the user's preferences; as in the case of the POI-TOI Scorer, cosine similarity was selected as similarity measure. Currently, CHIP does not provide explanations about recommendations to users; common explanation strategies on POIs rely on reviews text [15], which for less popular destinations may not be available in sufficient quantity or even at all, as in the case of the Umbria region. The numerical vector representation of POIs and user preferences according to the same TOIs, however, allows the categorisation of POIs according to its most representative TOIs. The main categories for recommended POIs could be presented to users and correlated to their preferences to explain the ranking choices. Furthermore, showing salient passages of POIs textual description which closely match the preferred topics could enhance the user trust in the system. Finally, to evaluate the recommendations quality, a user study is currently being designed.

2.3. Travel planner

The Travel Planner (TP) backend module computes personalised itineraries for users on the basis of their travel preferences, constraints, and the categorisation of POIs in the territory. The problem has been modeled as a Prize Collecting Vehicle Routing Problem (PCVRP) [16], a variant of the conventional Vehicle Routing Problem in which the number of vehicles available is not sufficient to serve all the destinations/customers. A selection criterion is employed to include a subset of the destinations only to both respect resource constraints and optimise one or more objectives, e.g., total profit collected, total travel time, total travelled distance. Formally, in a PCVRP, a complete weighted graph $G = (V, E)$ is built from the set of destinations plus a starting node usually named *depot*; each edge $e \in E$ is weighted according to a metric, e.g., Euclidean Distance, road distance, or travel time. A fleet of vehicles m is available to serve the destinations; each destination has an associated profit p_i and, under some formulations, an optional resource demand d_i. The goal is to maximise the total profit $\sum_{i=1}^{v} \sum_{k=1}^{m} p_i y_{ik}$, where $y_{ik} = 1$ if destination y is visited by vehicle k, subject to constraints, such as demand, time, and utilisation (all available vehicles must reach at least one destination). Furthermore, tours must not overlap, i.e., two vehicles must not visit the same destinations and all the vehicles must return to the starting point (the depot) at the end of the day. Such formulation is akin to that of the Tourist Trip Design Problem, in which single day or multiple, non-overlapping days itineraries must be planned to maximise tourists' satisfaction and respect trip constraints. A mapping from PCVRP to TTDP is naturally induced, by modelling each day of the trip as a different vehicle, POIs as destinations/customers, and the user-POI similarity scores as prizes for visiting POIs; round-trips from the depot mimic tourists' behaviour, departing from and returning to a fixed point, e.g., a hotel or country-house. This proves true especially in a small regional touristic context such as Umbria, where destinations are available at a fairly short distance. The CHIP travel planner employs an approach based on PCVRP, and handles the following constraints: maximum duration of a daily tour, maximum visiting time for a POI (i.e. filtering out POIS which require longer visits), number of days, lists of POIs that must be included in or excluded from the tour, number of proposed alternative tours, and transport mean, i.e., car, bicycle, or foot; the average visiting time required for each POI is factored in the itinerary computation. An adequate response time by the travel planner is required to improve the user experience, and therefore strategies are adopted to speed-up the calculation. On the one hand, a guided local search meta-heuristic allows escaping local minima while preserving efficiency[17]; on the other hand, POIs with similarity scores under a certain threshold $s_{min} = 0.5$, are excluded from the itinerary computation. The TP module of CHIP has been implemented with the *OR-Tools* library by Google [18]; to model prizes, a penalties mechanism is employed, by assigning higher penalties for excluding POIs with a high user similarity score. The travel distances between POIs and from the trip starting point, needed to build the complete travel graph, are provided by *OpenRouteService* [19] for each type of transport mean.

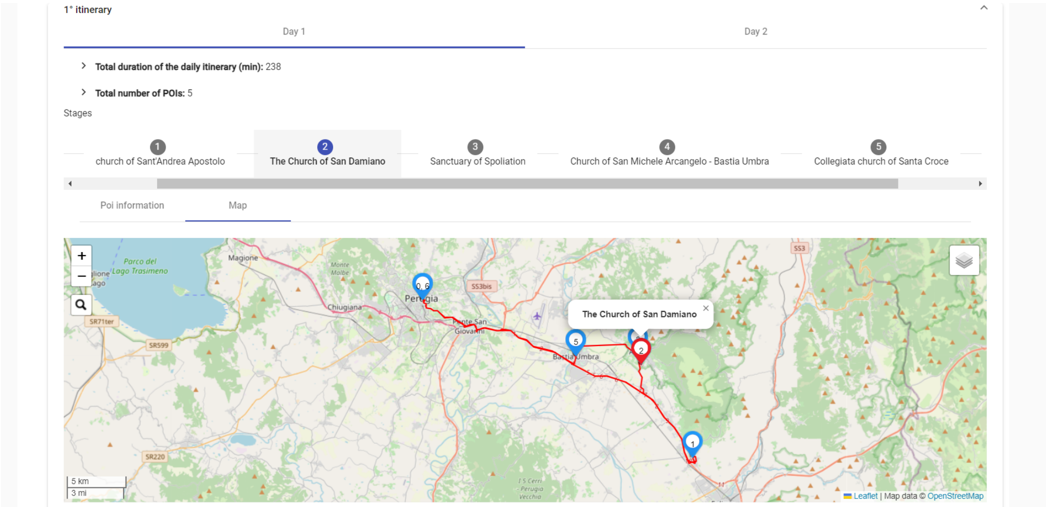

Figure 2: The tourist interface.

2.4. POI-TOI Manager

The POI-TOI Manager handles the communication between other backend modules and the POI-TOI database, where persistent data on POIs, TOIs, computed itineraries and users are stored; it centralises the database access logic, ensuring the correctness and execution of read and write operations.

2.5. Frontend modules

The frontend functionalities provide separate interfaces for end-users (i.e., tourists) and administrators-stakeholders. For the end-users the system offers the following functionalities:

- Expressing their preferences on the TOIs: with this information a user profile is created, which is then used by the User-Profile Matchmaker (see Section 2.2) to generate a ranking of the POIs that are most relevant and similar to the tourist needs;
- Expressing the user travel constraints (see Section 2.3); this information is used by the Travel Planner to compute travel itineraries to present to the user;
- Expressing a feedback on whole itineraries and single POIs (registered tourists only). This feedback is stored and will be used to dynamically adapt the user profile over time (the user profiling functionality is currently under development).

In Figure 2 a screenshot of the user interface is shown. After collecting preferences and constraints, the user is provided with a set of alternative itineraries; for each itinerary, the detailed travel plan for each day is visualized, both as an ordered list of POIs and as an itinerary on a map.

Administrators, instead, can manage POIs and TOIs within the system. They can gather knowledge about tourism dynamics to develop further insights and to modify information related to individual POIs, such as location, description, or visiting time. In addition, they will also be able to manage the different TOIs, ensuring that the information is always up-to-date and relevant. Changes made to POIs and TOIs trigger the POI-TOI Scorer module (see Section 2.1), which automatically recomputes scores between POIs and TOIs, thus ensuring an accurate and consistent evaluation.

3. Current and Future Developments

We presented CHIP, a Recommender System and Travel Planner for Cultural Tourism. The core modules of the system have been described, along with the user and administrator frontend functionalities. CHIP is currently tailored to provide travellers with robust, powerful, and flexible tools to plan personalised cultural itineraries in the Umbria region, based on their preferences. However, the architecture and techniques adopted by the system are general enough to replicate the service for other geographic regions, if sufficient data is available.

In the near feature we plan to extend the system with additional functionalities. In particular, the current user-profiling strategy, based on an initial user preferences collection phase, will be augmented with an explicit and implicit feedback mechanism on POIs and itineraries, to further improve user models. The current approach relies on computing accurate and robust latent representations of POIs and TOIs, a result achieved for a subset of the considered TOIs (see subsection 2.1); additional representation strategies are currently being tested for the POI-TOI Scorer module, e.g., employing advanced language models such as TourBERT, to better estimate the POI-TOI proximity. The combination of continuous user profile refinements through feedback mechanisms and accurate embedding mechanisms will further improve the quality of the recommendations provided to users; preliminary qualitative tests show that the planned itineraries already reflect the users' preferences. Further tests will be conducted, both before and after public availability of the system, to better assess the quality of the recommendations and improve them.

Regarding the chosen TOIs, administrators already have the possibility of changing existing TOIs or introducing new ones. The proposed approach can easily scale to a higher number of TOIs, provided that accurate and sufficiently long descriptions are available for TOIs and POIs, to compute embeddings; interrelated topics will likely be described by semantically related context words, leading to similar latent space representations and, subsequently, to numerically close POI-TOI scores. For such reasons, it can be expected that, using cosine similarity, the POIs would still be correctly matched to users, under the condition that the preferences expressed by the user are coherent with the semantics of the topics. However, it must be noted that requiring the user to rate a too high number of different TOIs may be detrimental to the user experience and induce confusion; perhaps more interesting is the possibility of dynamically changing TOIs with respect to the time of the year or promotional strategies planned by stakeholders.

Concerning the travel planner, the system will be extended to plan non round-trip itineraries.

Finally, in the broader scope of the RASTA project, new cultural heritage fruition strategies are currently under development to integrate VR/AR techniques, that will allow designing virtual tours to visit POIs and enable travellers to enjoy immersive experience during their trips. Finally, suitable Retrieval-Augmented Generation (RAG) techniques will pave the way for new storytelling experiences in which a POI narrates its history interactively.

References

[1] E. Commission, D.-G. for Research, Innovation, P. Brunet, L. De Luca, E. Hyvönen, A. Joffres, P. Plassmeyer, M. Pronk, R. Scopigno, G. Sonkoly, Report on a European collaborative cloud for cultural heritage – Ex – ante impact assessment, Publications Office of the European Union, 2022. doi:doi/10.2777/64014.

[2] F. Ricci, L. Rokach, B. Shapira (Eds.), Recommender Systems Handbook, Springer US, New York, NY, 2022. doi:10.1007/978-1-0716-2197-4.

[3] F. Ricci, Recommender Systems in Tourism, Springer International Publishing, Cham, 2022, pp. 457–474. doi:10.1007/978-3-030-48652-5_26.

[4] A. Bentaleb, Y. El Bouzekri El Idrissi, A. Ait Lahcen, A review on content based recommender systems in tourism, in: S. Motahhir, B. Bossoufi (Eds.), Digital Technologies and Applications, Springer International Publishing, Cham, 2021, pp. 527–541.

[5] C. Binucci, F. De Luca, E. Di Giacomo, G. Liotta, F. Montecchiani, Designing the Content Analyzer of a Travel Recommender System, Expert Systems with Applications 87 (2017) 199–208. doi:10.1016/j.eswa.2017.06.028.

[6] Z. Jia, Y. Yang, W. Gao, X. Chen, User-based collaborative filtering for tourist attraction recommen-

dations, in: 2015 IEEE International Conference on Computational Intelligence & Communication Technology, 2015, pp. 22–25. doi:10.1109/CICT.2015.20.

[7] M. L. Bai, R. Pamula, P. K. Jain, Tourist recommender system using hybrid filtering, in: 2019 4th International Conference on Information Systems and Computer Networks (ISCON), 2019, pp. 746–749. doi:10.1109/ISCON47742.2019.9036308.

[8] J. L. Sarkar, A. Majumder, C. R. Panigrahi, S. Roy, B. Pati, Tourism recommendation system: a survey and future research directions, Multimedia Tools and Applications 82 (2023) 8983–9027. doi:10.1007/s11042-022-12167-w.

[9] M. Fischetti, J.-J. Salazar-Gonzalez, P. Toth, The Generalized Traveling Salesman and Orienteering Problems, Springer US, Boston, MA, 2007, pp. 609–662. URL: https://doi.org/10.1007/0-306-48213-4_13. doi:10.1007/0-306-48213-4_13.

[10] H. d. Cros, B. McKercher, Cultural Tourism, 3 ed., Routledge, London, 2020. doi:10.4324/9780429277498.

[11] P. Vansteenwegen, D. Van Oudheusden, The Mobile Tourist Guide: An OR Opportunity, OR Insight 20 (2007) 21–27. doi:10.1057/ori.2007.17.

[12] M. Rigakis, D. Trachanatzi, M. Marinaki, Y. Marinakis, A hybrid firefly algorithm based on coordinates for the prize-collecting vehicle routing problem, in: E. Krassadaki, G. Baourakis, C. Zopounidis, N. Matsatsinis (Eds.), Operational Research in Agriculture and Tourism, Springer International Publishing, Cham, 2020, pp. 145–167.

[13] J. Ruiz-Meza, J. R. Montoya-Torres, A systematic literature review for the tourist trip design problem: Extensions, solution techniques and future research lines, Operations Research Perspectives 9 (2022) 100228. doi:https://doi.org/10.1016/j.orp.2022.100228.

[14] T. Mikolov, K. Chen, G. Corrado, J. Dean, Efficient estimation of word representations in vector space, 2013. arXiv:1301.3781.

[15] Y. Zhang, X. Chen, Explainable Recommendation: A Survey and New Perspectives, Found. Trends Inf. Retr. 14 (2020) 1–101. URL: https://doi.org/10.1561/1500000066. doi:10.1561/1500000066.

[16] J. Long, Z. Sun, P. M. Pardalos, Y. Hong, S. Zhang, C. Li, A hybrid multi-objective genetic local search algorithm for the prize-collecting vehicle routing problem, Information Sciences 478 (2019) 40–61. doi:10.1016/j.ins.2018.11.006.

[17] P. Vansteenwegen, W. Souffriau, G. V. Berghe, D. V. Oudheusden, A guided local search metaheuristic for the team orienteering problem, European Journal of Operational Research 196 (2009) 118–127. doi:https://doi.org/10.1016/j.ejor.2008.02.037.

[18] L. Perron, V. Furnon, Or-tools, 2024. URL: https://developers.google.com/optimization/.

[19] HeiGIT, Openrouteservice, 2024. URL: https://openrouteservice.org.