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Architecting Next-Generation Tourism Recommendation Systems: A Knowledge Graph Approach

Xiong Lei
City Graduate School, City University of Malaysia
Email: 3539114@qq.com

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Abstract

This work focuses on exploring the way to adopt Knowledge Graph technologies to innovate Tourism Recommendation Systems (TRS) for which the existing problem is on the aspects of data modularity and the capacity of algorithms. Using the conceptual framework of the Knowledge Graphs, complex relationships between the entities in the tourism domain can be better captured and used to improve the recommended actions' accuracy and relevance. In this way, Knowledge Graphs facilitate semantic understanding and real-time data integration to adapt TRS to the specific users' preferences and contextual characteristics. The paper aims at presenting different use cases of Knowledge Graphs in the context of TRS and the primary benefit they offer is the integration of different data sources to enhance the analysis process that helps travellers. Some major conclusions emphasize the role of Knowledge Graphs for extending TRS architecture, as well as analysing tendencies and further innovations to plans for recommendation in tourism. Finally, this research is valuable in the development of the theoretical foundation of TRS by assimilating recent IT advances to improve the level of satisfaction and quality of the travel experience.

Keywords: Tourism Recommendation Systems, Knowledge Graphs, Personalization, Semantic Understanding, Data Integration

Introduction

Over the past decades, the dynamic changes in technologies have affected the tourism area by enhancing the need for higher-level recommendation systems such as TRS that can conform to travellers' variety. Traditional TRS become problematic in the tasks of providing accurate and context-specific recommendations, because of limitations of the algorithms used, segmented and dispersed data, and the inability to change in real-time (Ahmad et al., 2024). In this chapter, knowledge graph technologies are introduced as a more viable solution for fronting the transformation of TRS that addresses the aforementioned challenges through the structured representation of relationships between entities in the tourism context. KGs help TRS to provide recommendations based on customers' preferences, contexts, and real-time information, thus increasing the efficiency and effectiveness of TRS. It is the most conspicuous feature of the modern trends that customer focus is vital for profitability in tourism. ZR TRS can provide exact recommendations by utilizing some other type of data like location and weather and through text mining to cluster the data for suggestions. KGs improve information comprehension and availability solving the difficulties regarding the development of TRS by integrating the data and with proper tools managing the structures. Research indicates that KG and ontology-based recommender systems are positive and proactive in the manner of traveller's decision-making through an efficacious combination of multi-source data and domain knowledge.

The problems of traditional TRS based on collaborative and content-based filtering are the inability to work with traveller preferences and conflicting, integrated, and constantly changing data sources in the tourism context. These systems claim to use algorithms to give users recommendations that sometimes are not relevant to the current situation or the user's preferences and history (Fayyaz et al., 2020). Such consequences of knowledge graphs as the integration of data of different types and origins, the search for implicit connections, and the provision of recommendations that are based on semantic analysis are the key benefits of the use of such systems. They optimize the speed of data processing in operational use and flexibility of application, thus providing better experiences to users. Tourism is doubtless an important sector that has been influenced by information technology improvements so that calls for better and enhanced TS. It is a fact that one can end up with a suboptimal solution in quite several cases, low-quality algorithms, a disjointed set of data sources, and sheer difficulties in adjusting to dynamic environments (Wahab et al., 2021). These shortcomings lead to providing rather abstract and vague recommendations aiming at the general population with little regard to individual variability and change, conditions and events in the destination they travel to.

It means, that TRS can use knowledge graphs instead of the old type of systems, like collaborative/content-based filtering ones which do not contain the possibility to integrate different data sources, such as location, and real-time feedback. It could be noted that knowledge graphs improve semantic understanding and have practical value for extending the results as they can be used for data mining and text analysis (Kejriwal, 2022). Concerning the aforementioned principles, one of the main advantages that can be pointed out about knowledge graphs is that it is a means for employing distinct data sources and managing the data which is rather difficult to process. Therefore, implementing the integration enables TRS to find relations between entities that have not been identified before, migrate probable future traveller preferences from historical data and get updated data in real-time – information that could be of use in evaluating the current situation of the destination. However, the recommendation models based on knowledge graphs integrate Difference also ontology-based recommendation models that tend to provide better predictions for the models since they use domain knowledge. This is because the above models not only discover the users' preferences but also represent them in the recommendation list with semantic-based recommendations that are capable of incorporating other factors that could affect the travellers' experience on their trip.

The foundation of this inquiry is informed by the following limitations when assessing the application of KGE to enhance TRS. Potential limitations include the fact that the analysed domain is complex and varied, numerous factors may affect tourism, and some questions may be more difficult regarding data availability and quality, let alone confidentiality (Rahmadian

et al., 2022). Even though it explicates the importance of TRS in teaching and learning, it does not provide directions for further reformative measures to be taken concerning TRS procedures, or how to handle developmental challenges. Other factors include: Limitation of time and funds also contribute to the restricted geographical coverage, shortage of inadequate and relevant data diction coupled with overstressing on the collection of data.
This study is confined solely to improving the subsequent generation of TRS with the help of knowledge graph strategies and does not incorporate other techniques or technologies. It limits its range to the tourism area, which results in the advanced consideration of issues and prospects in the recommendation system for tourism. The following limitations must be made about the study: concerning the availability and accessibility of data, sampling bias – resulting in the impossibility of using specific commercial databases – or limitations concerning realistic empirical testing, which inevitably reduces the depth of the analysis and the external validity of the results. The following temporal factors have also been considered: This is because technological development in the industry, and general changes regarding the field, may mean that the proposed TRS architecture may become irrelevant over time. Nevertheless, the following delimitations have been considered within the study to limit the scope of the research: Although it contains these limitations, the study intends to offer beneficial ideas concerning the enhancement of TRS efficiency, precision, and adaptability by applying knowledge graph technologies, which will help enhance the field of tourism recommendation systems.

The research objectives are demonstrated below

- To identify the strengths and limitations of existing knowledge graphs to enhance TRS efficiency for next-generation tourism recommendation systems.
- To develop a knowledge graph-based architecture for next-generation tourism recommendation systems.
- To enhance personalization and context-awareness in tourism recommendations through knowledge graph techniques.
- To address data fragmentation and integration challenges to leverage diverse data sources effectively.
- To improve real-time adaptability of tourism recommendations using knowledge graph approaches.

Literature Review

Recommendation systems are fundamental and crucial in dealing with large information overload more so in tourism through reflecting users' history and data. These systems that are based on the principles of AI and ML have gained importance primarily as a result of the growth of the internet that has led to the breakup or rather the overload of information (Hermann, 2022). First coined in the mid-1900s, the recommendation system is a system whose main purpose is to assist users in choosing the most relevant information from the many available, a task which is facilitated by the use of machine learning techniques. In tourism, these systems help the travellers by providing direction with specific data about the places of interest, thus facilitating more informed decision-making and better customer satisfaction. Yet, personal recommendation systems used in the current world utilize numerous filters, as well as data mining to enhance its performance and personalization. Recommendation systems in travel agencies as well as other related organizations are employed not only to suggest destinations but they are also to suggest packages for tours, routes for the tour and even hidden gems. The recommendation system relies on the features of the data mining techniques in that they analyze users' history of travel and recommend appropriate, alluring offers (Song & He, 2023). These techniques also help to re-generate the ranking of tourist spots and discover new hot spots. Filter and find algorithms are applied to the data of users to increase the effectiveness of recommendations in some contexts of utilizing pattern-matching algorithms. Also, rule-based data mining identifies the frequent patterns/associations/ correlations in large datasets and enhances the decision-making processes. Other complex approaches are used as the Hierarchy Sampling Statistics (HSS) and SVD++ algorithms. These methods collect information through questionnaires and ratings of some websites for tourists, for example, Smart Travel (Tavitiyaman et al., 2021). Due to these factors such as seasons of travel, interest or way of travel, such systems offer precise recommendations. Other user characterizing parameters include gender, age, and education level, and are also considered to split users into more consequent subgroups which will allow to use of the recommendations offered to reach a higher level of user satisfaction.

A knowledge graph also referred to as a knowledge model is a set of descriptions of relations, concepts, events, and entities interlinked. These descriptions include also formal semantics which can be easily read by both, humans and computers (Berners-Lee et al., 2023). Thus, knowledge graphs add up to one another so that they form a set of entities illustrating definite sections of the descriptions. It can also be noted that the described model utilizes the concept of a graph database, which is defined using labels, nodes, and edges. Nodes denote staking based on places, objects or persons and edges denote the relations between the said nodes. Specifically, nodes could be clients and agencies while edges could indicate relations of the clients and the agencies. The major ones are subjects (nodes), predicates (edges) and objects (labels). KGs are constructed from various data sources and are represented using identities, schemas, as well as Contexts. Identities define objects, schemas create a structure, and contexts define in what environment the knowledge is given (Boutyline & Soter, 2021). These components assist in demarcating semantic meanings of a word in different contexts, for instance in separating between the computer developing company Apple and a fruit. Semantic enrichments are employed in the construction of knowledge graphs using machine learning and natural language processing to develop label, edge and node views. This makes it easier for them to point out connections and associations within the data, which helps in carrying out activities such as responding to queries as well as assisting the business in its decision-making process. The form combines the datasets to arrive at new knowledge relationships by finding the features that were not noted before, improving efficiency and creativity. The uses of knowledge graphs extend to the fields of retail, entertainment, finance and banking, tourism, and healthcare. In retail, they distinguish customer needs and suggest appropriate products. In entertainment, Netflix and Amazon Video are some of the platforms that employ them to recommend materials based on the client's interests. The finance sector uses knowledge graphs more actively due to the fight against crimes and customer identification (Nicholls et al., 2021). In tourism, they contribute to recommender systems, while in healthcare they reflect on the structure of data and the treatment of patients by considering their requirements and research in the field. Knowledge graphs link the data are valuable for organizations and help enhance service delivery in various fields.

Social filtering techniques such as collaborative filtering and content-based filtering analyze the customers' preferences and give useful recommendations. Based on the interest or behaviour of a user, the graph formed helps in improving management decisions. While knowledge-based systems only utilize firsthand knowledge for recommendations the social, and content-based systems also use other resources to give a full list of recommendations. The protection of data is integral in TRS to uphold the trust of users and be in line with the laws on data protection to avoid cases that may jeopardize travellers' information. Visualizations attract the user by giving real-time location details and tourist sites through smart devices (Farmanbar & Rong, 2020). As the remarkable visual content gains the clients' trust and contributes to better decision-making. By the objectives of TRS, the accessibility and the use of the system in terms of providing detailed item descriptions are optimized. Some of the social networks that play a crucial role include Myspace, LinkedIn, & Facebook as they collect the users' details and increase the preciseness of the recommendations. Mobile and web integrated part in TRS recommends real-time response, it uses ICT tools and the Internet of Things for better service delivery. Current scalability issues are resolved with problems of high loads from users and the sparseness of data tackled with reliable algorithms. User history interaction with TRS provides the analysis of the search preferences which enables refinement recommendations as well as provides a better understanding of the users' preferences under certain contextual conditions which improve the overall travel experience. Today the focus is on technology and data, and undoubtedly, the availability of the Internet all over the world has been a factor in the information explosion (Singh et al., 2022). This requires systems that sift out relevant information from large information volumes, especially in the tourism domain. Different types of recommendation systems have been introduced to assist users in filtering the information and products that are more to their taste in terms of their profile and past activities. The former of these systems use machine learning algorithms to suggest appropriate tour packages and travel destinations. Recommendations of personal tourism are the special systems that apply users' interests and suggestions for unvisited places, as well as boosting the decision-making speed. The most common is collaborative filtering where an essential aspect of users' interests and their behaviour is identified to raise the systems' performance. The recommendation further involves the process of data mining that helps in extracting all the required information from the large data sets so that tourism can be managed effectively and the communication services for the tourists can be enhanced. E-tourism systems especially in a country like China, integrate and bring efficiency to the processes as well as smart tourism solutions (Wang et al., 2022). This system offers specific information, instead of overwhelming users with loads of information and enabling them to carry out proper planning of their trips. Filtering techniques including collaborative, content-based, social, demographic, knowledge-based, and utility-based hybrid techniques are used to extend the recommendations to the users. Recommendation systems for tourism enable users to find destinations and services they are recommended to visit or use, give feedback and rate services. These ratings are useful for ordering destinations and accommodations and become helpful for those who are going to travel in the future. The system employs collaborative and knowledge-based filters to produce compatibility between the user's profile and the destination attributes analyzing the constraint such as the amount of money and time of travel (Özdemir, 2022). Another feature of agent technology is involved in gathering and analyzing the recommendations to provide the best suggestions to the user to bring about a general enhancement of the travel experience.

That's why a knowledge graph, or a semantic network, is a graph structure that directly depicts events, concepts, and objects from the real world and the connections between them. It comprises nodes, edges, and labels: nodes are the integrated part that depicts the corresponding elements of the model: places, persons, objects, etc.; edges define the interaction between nodes; and labels split nodes into categories. Concepts employed in knowledge graphs are from different sources and thus, the structure is more fluid than that of relational databases (Weikum, 2021). They employ semantics for the data enrichment by using machine learning and natural language processing techniques. KG improves tourism recommendation systems due to the efficient modelling of data regarding events, venues, and users' preferences. First, they are involved in data integration, second, they generate new knowledge, and third, they make links between often seemingly unconnected data sets. Recommendations are easily made when there are nodes, edges and labels so that information is fully captured. These graphs are essential in various sectors, solving problems connected with big data integration and retrieval. In tourism knowledge graphs help to optimize the users' interactions by offering them personalized results (Fensel et al., 2020). They include identifying destination, accommodation and other aspects that relate to the user's preference. Units store organizational information and link two users; these are objects and other entities that prevail in an organization.

These are known as entities, and the labels categorize them; these and the edges that represent relationships help recommendation models. Recommendation systems with knowledge graphs enhance the propagation of information between the nodes of the graph as they solve the link prediction challenge by employing graph neural networks (Gao et al., 2023). This method also improves how fresh sources of information can be incorporated without necessarily forcing the creation of an organisational hierarchy. In tourism, nodes refer to the interest of the user and details of the destination to help in choosing the tourist destination as well as providing background information. The function labels served for understanding and relations between entities, and the edges' mean leads to higher quality recommendations.

Over the last couple of decades, the industry of tourists has greatly expanded mainly due to the improvement in communication technology and information technology due to the increased use of the Internet. This evolution has made the search for international data easier and enhanced the points of interest travel plans, and destinations for potential customers (Paulino et al., 2021). E-tourism as a new type of tourism has significantly impacted the social and economic segments of tourism, predetermining a large amount of data to assist tourists in their decisions. With the current era of globalization and development, Recommender Systems (RS) has a significant impact as a weapon for customer's assistance in choosing credible service providers like hotels, tours, tickets, and restaurants. Demographic information and received reviews and feedback are used by these systems to estimate and suggest proper holiday packages. RS can be viewed as fitting into the wider context of information filtering, which significantly improves customer satisfaction rates thanks to the closer relevancy of the offers provided (Yıldız et al., 2023). The second relatively new concept is Smart Tourism, which is based on the application of Information and Communication Technologies to develop new innovative tools and approaches in the sphere of tourism. This approach focuses on enhancing the logistic, environmental, and economic efficiency and the touristic experience using the Internet of Things, mobile communication, cloud computing, and artificial intelligence. These tools implement the consolidation of the frameworks to lower data silos, thus improving service quality and customer satisfaction. Gradually, the creation of software agencies and web-based platforms improves the interaction of customers with the tourism industry. Such platforms employ agent technology and multiagent systems because these approaches generalize the relationships and facilitate the integrated-data-driven decision-making process (Júnior et al., 2021). To effectively address data silos, hence compromising the amount of information sharing within an organization, data management is achieved significantly to enable the smooth running of tourism businesses as they offer their recommendations to travellers. The tourism sector has experienced growth with the help of the development of technology and the internet making it easy for tourists to get information on world tourism and the capabilities of the e-tourism sector. Tourism displayed dependence on Recommender Systems (RS) as a result of the integration of artificial intelligence and machine learning since knowing graphing offers individualized recommendations.

Theoretical Framework

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) created by Fred Davis in 1986, is the fundamental model for the study of user's acceptance of technology. According to Rafique et al (2020), TAM focuses on two key aspects: and two constructs; perceived usefulness and perceived ease of use. Perceived usefulness measures the degree to which individuals believe that the implementation of technology will increase their productivity and efficiency. Concurrently, perceived ease of use focuses on the extent of readiness of the user in terms of how easy it is to operate the technology element in question. All these matters relate to user attitude and behavioural intention regarding the use of technology especially in scenes such as that of the tourism industry where the recommendation systems are bedrock. In the case of the tourism recommendation systems, the applicability of TAM is in its predictive power of the user's intentions triggered by perceived usefulness and ease of use. Natasia et al (2022) argue that incorporating TAM increases the usage of recommendation models to engage and satisfy users since it maps technological characteristics to the users' perceptions. However, there are disadvantages, for instance, security threats that require enhancing the model algorithms for the users and increased efficiency of the system. The websites' applications and contacts have continuous overall updates and impressive interfaces that prevent bad implications and sustain good consumer experiences (Han & Sa, 2022).

Behaviourist Theory

Behaviourist Theory originated in the early twentieth century to strive for the explanation of human behaviour by using stimuli and environmental responses behaviourism states that behaviourism is a theory that holds the view that behaviour results from previous experiences and influences from the surroundings. Of relevance to tourism recommendation systems, this theory assists in understanding how users' behaviour changes over time due to the change in technology and interaction with the system. Burhanuddin et al (2021) notes that one of the strengths of behaviourist theory is in defining an individual's behaviour patterns and those are precisely the elements necessary for enhancing the accuracy and timeliness of recommendation models in the complex field of the tourism industry. The models using the data of the feedback and responses from users allow knowledgeable recommendations towards further destinations and experiences attractive to the user. In addition, Stewart (2021) hold that appetitive principles also help the recommendation systems provide a clear demarcation of negative and positive experiences shared by the users. Feedback feedback strengthens recommendations given to similar users while negative feedback induces modification to the product to be recommended in the future. This process not only improves user experience but also increases the value of the whole travelling experience to suggest offers that are relevant to the real-time input provided by the user.

Conclusion

Due to the innovation in technologies in the tourism industry, complex TRS that meets the various needs oftravellerss is required. Some of the problems that hinder the efficacy of traditional TRS are,e for example, the limitation of algorithms in recommending data, scattered data and information, among others. This chapter presents Knowledge Graph technologies as the solution that will revolutionise the TRS since it allows expressing the complicated connections within the tourism area. Due to the incorporation of heterogeneous data and appropriation of semantic awareness, the performance of TRS is improved by Knowledge Graphs. They recommend items based on individual user choices and the current conditions using data that was previously ignored by traditional recommender systems. In the next steps, the utilization of Knowledge Graphs can transform the subsequent processes of TRS by addressing the issues of data consolidation, customer experience, and the tourism industry's development.

Contribution

This research therefore greatly assists by engaging the evaluation of Knowledge Graph technologies in the improvement of TRSs. They discuss important issues that the conventional TRS has, namely, the algorithmic issues and the disintegrated data, and present the potential solutions with the help of the Knowledge Graphs. Using semantic interfacing and data analytics in the present work – has outlined how the Knowledge Graphs have made recommendations about the users' preferences and contextual environment in real possible. In implementing TRS architecture, the study results suggest that Knowledge Graphs play the role of a breakthrough in the fields in question, as well as an important factor in improving system flexibility and user satisfaction. Thus, this contribution contributes to the theory of TRS with the integration of advanced technology which opens up for further development of customised recommendations of tourism and satisfying travel experience.

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