

A Systematic Survey of Tourism Recommender System Techniques and Challenges

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Abstract

Since the epidemic, there has been a significant drop in the tourism sector, thereby affecting several tourism-dependent nations. However, after COVID-19, people have been wanting to go out to visit places. Since the online era has been trending, people might take help from some websites that use recommender systems to suggest the desired destination which includes basic amenities like the places to visit, hotels, traveling, food, etc. to the user. This paper focuses on some key ideologies that are mostly used in most of the user searches. It discusses the latest machine learning and deep learning techniques used in tourism recommendation and the challenges that are being faced to date by the recommender systems. Recommender systems help to organize a large amount of data available online just by getting the reviews and looking at the previous history of the users. The latest papers have been classified and the papers are analyzed and categorized according to their applications.

Keywords: Cold-start, Cultural Heritage, Real-Time, Social Media, Sparsity, Tourism recommender systems (TRS)

1. Introduction

Most of us like to travel for vacations or go out on a holiday. All of us crave for a good outing sometimes. Defining tourism might be tricky, but can be understood as a social, cultural, and economic phenomena that involve individuals, visitors who may be tourists, residents, or non-residents, traveling to nations or locations beyond their typical surroundings for reasons that can be personal or professional. Tourism, especially in India, is vital to the economy of the country as it itself ranks 10th out of 185 nations in terms of overall GDP

contribution [1]. According to WTTC, this sector supported 39 million jobs in 2020, which are almost 8 percent of overall employment and is expected to support about 53 million jobs by 2029. Travel and tourism industry is both dynamic and competitive. This sector needs to compete with the growing demands and wishes of the client, since what comes first is customer happiness. Entertainment and safeguarding the whole tour are particularly important to tourism enterprises

Smart devices are a great help with route navigation and looking for popular destinations. The industry has been revolutionized with the human-smartphone interaction [2]. This sector needs to be hired with communities and individuals to ensure the success of tourism which can lead to a win-win situation for both the industry and the people being hired by it. Therefore, tourism development as well management processes require significant continuous transformation.

Recommender System (RS) being a part of information filtering system, helps in filtering all the information stored online about any person to help him/her find a suitable place to visit. Researchers have introduced several recommendation programs to date, each with a different purpose [3]. Some programs aim to recommend travel packages, some recommend the best destination to go depending on user preferences, others recommend best travel options etc.

In section I, a brief overview of tourism and its present state is discussed. Section II discusses the background of recommender systems and the popular types which are widely used. Section III talks about tourism recommendation and is further divided into several sub-sections discussing the key ideologies, various recommendation techniques used for tourism recommendation, frequently used datasets and evaluation metrics. Latter section displays the recent challenges faced in the recommendation for the researchers. In the last section, the lessons learnt from this survey are illustrated.

2. Background

In the past few years, the boom of an online era has made recommender systems more involved in our daily lives. The advent of internet has led to a boom in the online social networks. This boom in online social networks has led to an increase in various online services and multimedia tools and techniques [4]. From any online streaming services (Netflix, Amazon, YouTube etc.) to e-commerce and online advertisements, everything uses

recommendation systems to show the relevant searches that the user may prefer. In a simplified way, the recommendation system can be looked at as an algorithm which helps in suggesting relevant items to users. They are also critically important in some of the industries as they help to make a huge amount of income by being efficient and by standing out from other competitors.

There are various innovations in the field and different techniques when implementing these recommendation models. The popular aspects can be classified into four types as Collaborative Filtering (CF) based, Content based, Context based and Hybrid recommender systems [5]. Collaborative Filtering recommend users by using the other people's reviews as the data to make suggestions to the users for their next trip. It is most likely to happen that if someone has agreed on a certain rating in the past then he/she will agree on the ratings in the future too, by putting in more faith in the suggestions that are given by the other people on the internet.

Content Based filtering relies on the ratings and reviews given by that user in the past to similar products. Matches are calculated based on their similarity in terms of features. This form of recommender system seeks to be able to get features or behaviour that are purely based on the qualities of an item to which he or she responds favourably.

Context-based approaches provide users recommendations employing context in their computations to forecast what the user may most likely be interested in. These calculations of prediction depend on the user's, item's, or interaction's circumstances like Geographic location, weather of the destination, or previous siting records [6]. These are then utilized to describe the state of the things that may be used to create the environment in the user application contact. Many gadgets like mobile phones, or smart wearables have internet connections making them readily accessible nowadays [5]. These gadgets are utilized to gather and offer a plethora of information that can improve the present environment and its variations.

A hybrid-based recommender system is a form of recommender system which consists of all the other kinds of recommender system. Hybrid based recommender system is most used RS as it consists of all the RSs, and it also helps in overcoming the limitations of the individual RSs and only uses their strengths. During the generation of suggestions for the target user, every traditional recommendation technique suffers from several issues such as cold start, sparsity, and scalability.

3. Tourism Recommender Systems

In the tourism sector, the goal of a recommender system is to identify and suggest the best possible trip covering maximum Point-Of-Interests (POIs) of the user based on the provided factors. These POIs certainly vary from one individual to another due to time constraints and personal preferences. Tourism recommendation covers recommendation of hotels, mode of transports, restaurants, sites to view for a comfortable and budget friendly trip [7]. Furthermore, it helps in narrowing down eligible POIs for selecting as well as planning acceptable order and length of trip customization in unknown locations. Tourism recommender systems have become appealing to travelers, but difficult for designers to implement since they must be able to deliver individualized services. Many tourist recommendation methods have been explored in order to provide users with items that are relevant to their interests. However, including multi-criteria ratings and different cultures, which have a considerable impact on users' opinions of tourism facilities into recommendation systems, is a difficult challenge.

3.1 Key Ideologies

The survey includes up-to-date research on how recommender systems implement smart tourism destination principles. The 'core ideologies' of the smart tourism industry maybe recognised as the foundations of comprehensive investigations. These concepts (Fig. 1) demonstrate significant contributions to the tourism sector.

Big Data is renowned for its massive volume, fast velocity and complexity which is almost next to impossible to process if incorporating traditional methods. Its diverse and vast data are recognizable when talking about tourism data. Rapid pace of its growing applications in tourism and POI related content has been fuelled by technological advances in database systems and diverse software. It has now become viable because humongous data can be easily obtained for external sources like social websites and media. Even the advanced technology is accessible which ultimately allows the data analysis for researchers [8]. For building smart tourist information systems, the first and foremost cruciality is to recognize the features of big data. It follows up with addressing issues in order to develop a successful app. These can result in customized trips plans and suggestions that are tailored to the taste of the tourists.

Context-Awareness, according to Information Technology, refers to solve real problems by applying the prior knowledge gained by getting aware of the actual environment

in which the supposed computing system operates. When a computing system, such as a Smartphone sensor, has specific location data, it may limit the results of searches or queries to data that is relevant to that context. The information gathered has a significant impact on the services provided by smart tourism information systems. In the tourist arena [9], researchers have pointed out the benefits of adopting decision-making approaches based on contextual data.

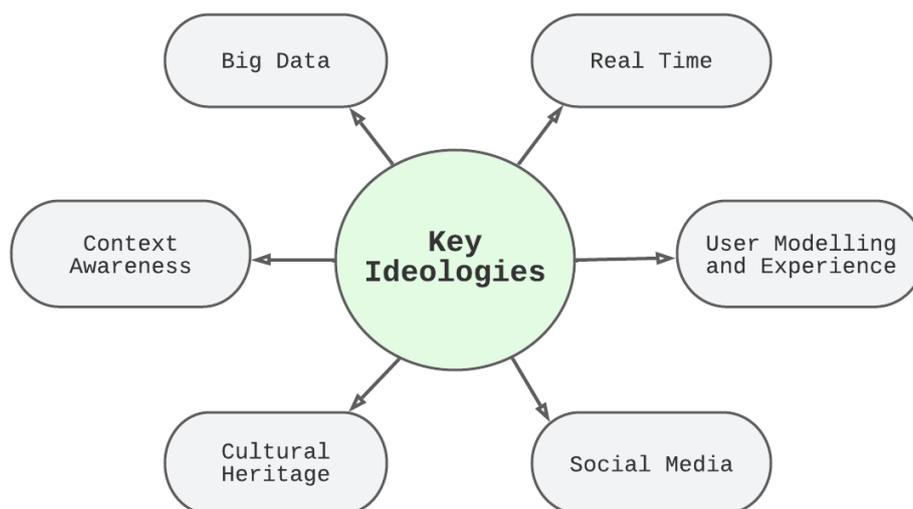


Figure 1. Various Ideologies used in Tourism Recommendation

Cultural Heritage has a high importance both nationally and internationally since it helps people to learn about a territory's cultural roots, memories, and identity. The paper [10] offers a cultural heritage recommender system, an android-based application, that can assist tourists in selecting destinations to visit, picked according to the interests of the target users and the current situation in the region, and that can consolidate knowledge of the places visited. Its integration is a prominent topic for improving the tourism sector. Social Media is tied to both technology and big data since it was made feasible by the creation of platforms that allowed individuals and businesses to communicate. User-generated comments on social media are one source of big data for customer analysis. The smartphone camera is the next social media game changer. Today, more than a billion people worldwide own a smartphone, which means that many tourists have a video camera in their pockets [11].

Customers no longer need to create a costly and time-consuming music video to convey a terrible service experience; instead, they can just record an occurrence in real time and publish it on social media. Social media plays an incredibly vital role in planning of

vacation for today's generation. Leading social media services like Instagram, Facebook, twitter & reddit have become the go-to stop for travel recommendations. Hashtag labeling, popularized by Instagram, aids by providing information about current trends and geographic locations.

Smart tourist information systems' Real-Time requirements, such as synchronization, time dependence, and user awareness, are three major components that play an important part in treating the ideologies as a whole. The construction of a real-time tourism information suggestion system on a smart phone employing responsive web design is shown in the study [12]. Temporal and spatial ontology databases are proposed, which collect tourism information such as tourism destinations, restaurants, hotels, festivals, and traditions.

The term "User Modeling" refers to the process of identifying comprehensive data depending upon the behavior and needs of system users. Even after including all the complex features and models in smart tourist information systems, the system demands a great and pleasant User Experience. It depends on the design and build of the smart device. This will leverage efficient and more interaction of the individuals with the smart tourist information device. A functional tourism system is offered which provides a highly recommended application that the potential individuals may use, and its evaluation is favorably and long drawn out [13].

3.2 Recommendation Techniques

Tourism recommendation incorporates various recommendation techniques for creating the best first list of suggestions or planned POIs to forecast the desired trip or other tour related suggestions like hotels, restaurants or mode of transport. Table 1 shows how different recommendation techniques have been employed in distinct methodologies for suggestion. Mostly neighbourhood-approach is used to select a group of people whose taste is similar to the user for whom recommendations are given. A weighted average is provided in the form of predictions or recommendations of the actions or ratings of this group. The weight is defined by the interdependence seen between the individuals actively utilising it and its surrounding members. A recommendation model keeping preciseness of tourist attractions is based on Weighted CF algorithm which searches for optimal shortest path and can save traveling time and cost [14].

The prediction of missing values in any model is a difficult task and is both well applied and predicted by incorporating HOSVD [15]. These predicted performances are later

tested with CF based approaches and multi-criteria recommendation methods for tourism. A natural limitation of the CF is the cold start problem i.e., when there is not enough data about the user and the algorithm cannot select a similar group of people to give suggestions to the user about the products. SVM-GBRT [16] has stronger generalization and multisource information adaption abilities outperforming other memory-based techniques which suffer from cold start. There have been improvements in several performance metrics such as F1-score and precision of PMF model while taking into account features like visual parameters [7].

Textual data and photos uploaded are the main source of user generated content data. Textual data that can be extracted from blog, comments, etc. are mainly used for extracting tourist sentiments and tourism recommendation [17]. User text reviews are an excellent supplement to user ratings for determining user sentiment. Apart from that various social media services like Facebook, Instagram, Flickr, Twitter has communities and groups where people share their experiences related to their travel, and valuable sentiments can be extracted from these resources. A sophisticated Tourism recommendation system is proposed by using user sentiment pattern and applying into SVD++ (Singular Value Decomposition) model [18]. The photos uploaded by tourist in comparison to textual data can provide better array of information, because of visual aspect it provides better spatio-temporal attributes [29] which can be used as an important parameter and can help further in improving the recommendation.

A personalized AR based Tourist recommendation system [20] is proposed that works in two parts. Firstly, the user's interest prediction is forecasted based on its demographic context and then utilizes decision making methods like VIKOR and SWARA to retrieve the data for the user taking into account factors like time and distance. The researcher can use hybrid recommendation models as a better method to handle these issues. Incorporating the user's contextual knowledge is quite beneficial in resolving individuality concerns [30]. To solve problems like cold start, sparsity etc. context-aware RS, a unique hybrid solution has been developed that integrates association rules, community produced information, probability measurements, and semantic web technologies [31]. Another novel approach HLTRS [23] has been proposed. HLTRS also solves problems like cold start, sparsity. This approach focuses on user individual profile data and group activity data acquired from the social network location based, HLTRS creates a separate profile for forecasting POI for particular user.

Table 1. Recommendation techniques used in recent research papers for tourism recommendation

Approach	Recommendation Techniques	Features	Limitations	Citations
Collaborative Filtering	K-Nearest Neighbors Co-clustering SVD SVD++ Non-negative MF Probabilistic MF ABMCR SIFT Bayesian Classifiers SVM-GBRT Neural Networks One-vs-Res	No Domain Knowledge is necessary Quality is adaptive	Quality is dependent on a large historical dataset Unable to handle fresh POIs Hard to include side features for POIs	[14], [15], [7], [16]
Content-Based	SVD SVD++ HTF TopicMF TimeSVD++ RPS SYN-ST SVD++ Relevance Feedback Genetic Algorithm	Scaling of a large number of people is easier and no need for other users' data Identify cross-genre niches	Domain Knowledge is necessary Limited ability to expand as per user's existing interests	[17], [18], [19]
Context-Based	SWARA VIKOR Clustering Support Vector Machine Bayesian Network Popularity User-based CF UCF+G GeoMF HSR ASMF-LA HGFM HiRecS	Selection of approach largely depends on the service needs Mostly application bounded and runtime operable	Retrieval of data is computationally expensive Not scalable Performs better in lesser complexity	[20], [6], [21], [22]

Hybrid	ACO MWO CSA HLTRS CoRec NECTR K-Means effect KATZ Jaccard Adamic-Adar Random walk TME-P Apriori Emotion-Aware RS	Significant information is considered for POI recommendation Helps in overcoming problems like Cold Start, Sparsity, and Scalability	Mostly depends on the implicit feedback data and not on online recommendation	[23], [24], [25], [26], [27], [28]
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SVD → Singular Value Decomposition,

MF → Matrix Factorization,

ABMCR → Aggregation-based Multi-Criteria Recommendation,

SIFT → Scale-Invariant Feature Transform,

GBRT → Gradient-based Regression Tree,

HSR → Hierarchical structures MF,

UCF+G → User-based CF integrated with geographical information,

ASMF-LA → Augmented Square Error-based MF,

HGMF → Hierarchical Geographical MF,

HiRecS → Hierarchical Contextual Location Recommendation System,

ACO → Ant Colony Optimization,

MWO → Mussels Wandering Optimization,

CSA → Cuckoo Search Algorithm,

HLTRS → Hybrid Location-based TRS,

NECTR → Neural Encoders Combined with Tensor Decompositions for Recommendations,

TME-P → Then Part and Missed Hits Emphasis Popularity-based

3.3 Datasets for Tourism Recommender System

Tourism data gives comprehensive information about tourist check-ins data, flight data, geotagged images, reviews on attraction sites, restaurant reviews, etc. A list of most frequently used dataset in domain of tourism recommender system has been created (Table 2).

Table 2. Most frequently used latest datasets in tourism recommender system

S.No	Dataset Name	Description	Dataset Link
1.	Yelp Open Dataset	Yelp dataset is a huge subset of user reviews, business listing, user data and photos. It comprises of 6.9 million+ reviews, check-ins data of over 131 thousand businesses, 200 thousand+ pictures.	https://www.yelp.com/dataset
2.	Yahoo Flickr Creative Commons 100M	YFCC 100M dataset contains over 100 million media items i.e. 99.2 million photos and 0.8 million videos. It also contains over 48 million geo-tagged images.	https://webscope.sandbox.yahoo.com/catalog.php?datatype
3.	Google review ratings on attractions across Europe	User ratings from Google reviews are used to create this data collection. Attraction reviews from 24 categories across Europe are taken into account.	https://www.kaggle.com/ishbhms/travel-review-ratings
4.	Travel and tourism data by the Indian Govt.	Archive of various tourist visit dataset and tourism projects managed by Indian Government.	https://data.gov.in/sector/travel-and-tourism
5.	Travel Reviews Data Set by UCI ML Repositories	TripAdvisor.com was crawled to create this data collection. Reviews on places in ten categories from all throughout East Asia are taken into account.	https://archive.ics.uci.edu/ml/datasets/Travel+Reviews
6.	A synthetic dataset of corporate travels	This dataset consists of travel related data. It provides the travel IDs as well as other flight related information.	https://www.kaggle.com/leomauro/argodatathon2019
7.	Travel dataset by data.world	This dataset contains open data provided by thousands of people and organizations about travel all across the globe.	https://data.world/datasets/travel

3.4 Evaluation Metrics

Effectiveness of tourism recommendation systems is measured using several metrics. Some of the most used metrics are discussed in this section. Precision is defined as the quality of the positive recommendation made by the recommender system. The ratio of True

Positive (TP) recommendations and Total recommendation of positive nature which consists of true positives and false positives (FP) defines this quantity. Precision is defined as follows:

$$precision(p) = \frac{TP}{(TP + FP)} \quad (1)$$

Relevancy of the accompanying dataset is determined by recall. Recall is computed by taking ratio of true positive recommendation divided by the true positive recommendation plus false negative (FN) recommendation. Recall is defined as follows:

$$Recall(r) = \frac{TP}{(TP + FN)} \quad (2)$$

F-score integrates recall and precision into a singular entity, illustrating their properties. F-score is defined as follows:

$$F - Score = \frac{2 \times p \times r}{p + r} \quad (3)$$

For ranking the recommendation, precision and recall are both ineffective. Mean Average Precision (MAP) [3], [16] overcomes this issue and efficiently calculates the effectiveness of recommendation systems. MAP@n is defined for top n recommendation as follows:

$$MAP@n = \frac{\sum_{i=1}^{N_q} AP_i}{N_q}, AP_i = \frac{1}{r} \quad (4)$$

Average precision for i^{th} query is denoted by AP_i , total number of query is represented by N_q , and correctly labelled rank is denoted by r in the output list.

4. Recent Challenges

Even after so many advancements in the types and models of recommender systems, there still are some common challenges that are faced by users and researchers in the field. Some of these challenges and limitations are discussed in this section:

4.1 Refined Transport Data

The mode of transport plays a crucial role for trip planning. A user might consider different forms of transportation based on their preferences. There are several modes of transportation available, including foot, bus, rail, taxi, and vehicle. It may be used by tourists

to visit a location [32]. So, more data related to transportation can improve the recommendations and can help tourists to better plan their trips.

4.2 Change in user Preferences

Users might have active changes in preferences which can lead to inaccurate results. So, user's preferences, similarity frequencies, interests must all be recalculated by the recommendation system to keep up with changes in user preferences [32]. Such real time factors can be incorporated to make accurate/ personalized planning of a user's trip.

4.3 Data Sparsity and Cold Start

The problem with data sparsity can be highlighted by the fact that collaborative recommendation systems rely on user [33]. Furthermore, in other situations, even if a product gets strong reviews, it is not recommended. If the number of reviews is low, it may also lead to poor recommendations for new users or users with different preferences. Even if it is a good product, it may not be recommended since a small number of individuals have used it or given it a positive review. For example, a new tourist attraction may not draw many visitors just because it has a tiny number of reviews. In the Cold Start challenge [34], [35], however, recommending to new customers is problematic because there is no prior history of their reviews on other products on which to base new recommendations. Even if a recommender system asks users about their preferences if they are new, the products may not be satisfactory because the exact parameters are not met.

4.4 Time-awareness

It is a common collaborative recommender system limitation in which the recommender system ignores the time of purchase of the product and simply recommends products on the review history of users online. The preferences of a user may change throughout time. For example, if a user wants to visit a destination in the summer but ends up getting a recommendation for a different location with different weather simply because of the popularity (better reviews and search history) of that product on the internet [36].

5. Research Gap and Discussion

Many researchers are looking for solutions to issues in context-aware cultural heritage applications, so integrating cultural heritage with current technology is a hot topic. Modelling the user-hotel interaction in a Poisson distribution, which incorporates the long-tail of users

and hotels, can be used to ease the data sparsity problem of time-aware recommendation [37]. Temporal dynamics, as well as semantic information, can help improve hotel suggestion performance. The need for increasing privacy and security considerations are recognised while developing new recommender systems as the degree of customisation and contextualization increases.

After analysing the last five years of research publications, it is discovered that Hybrid recommender systems can overcome most of the challenges that the other recommender systems encounter. Most of the studies either leverage the existing technologies or use new hybrid algorithms with other combinations of MF techniques like k-means, SVD, and PMF. Based on this finding, MF model is the primary approach employed. Improvements are noticed in several performance metrics such as F1-score and precision of PMF model while taking into account features like visual parameters.

6. Conclusion

This review article provides a comprehensive literature review structure. The work aims to provide an overview of the existing research that has been conducted in the tourism sector, as well as a thorough analysis of the components of the tourism recommendation system. It is suggested that contextualization should be expanded to several dimensions for all the travellers, including food, budget, transportation, weather, accommodations, and all the other individual travel preferences, by combining various types of essential ideologies and data available through internet communities. Four different types of recommender systems which have been applied in the tourism industry, namely collaborative, content, context, and hybrid have been examined and its recommendation techniques, features, limitations, and previous work regarding the recommendation systems are discussed. It is vital to employ hybrid approaches as they not only give particular treatment, but integrate many other strategies to construct a RS that can overcome the difficulties like data sparsity, cold start and dynamic preferences and improve the performance of other recommendation techniques.

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