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Review Article

TOPIC MODELLING-ENHANCED RECOMMENDER SYSTEMS IN TOURISM

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Abstract: *The development of information technologies has enabled the distribution and availability of information globally, which is reflected in all social spheres, especially tourism. A vast amount of information about tourist offers is available to travelers daily, often overwhelming users and leading to information overload, making it significantly difficult to find the offer that best matches their preferences. Recommender systems, an artificial intelligence-based technology, can help users make decisions by guiding them in a personalized way. By matching user preferences, they offer timely and relevant suggestions for destinations or tours and save time and cognitive load during the selection process. Recommender systems can be beneficial for tourists and tourist organizations, but their implementation is not straightforward. Numerous different challenges can occur. Some of them are caused by multipolar nature of tourism like language and spatial barriers, seasonality and preference variability. Others can be common recommender system problems such as cold-start, sparsity, explainability, accuracy and others. Topic modeling can help address these challenges by extracting topics from textual data, which provide valuable insights and enhance effectiveness of recommender systems. This paper aims to describe the development challenges in tourist recommender systems and present how topic modeling can address these issues, benefiting both tourists and businesses in the tourism sector.*

Key words: *recommender systems, tourism, topic modeling, multipolarity in tourism*

JEL classification*: L83, Z32, C38*

1. INTRODUCTION

The advancement of information technologies and the vast accumulation of data have contributed to the development of society across all domains, including education, healthcare, culture, politics, science, etc. One of these fields is tourism, where a significant number of individuals actively share and search for tourist information. As globalization increasingly eliminates national borders, and tourism by its very nature is not limited to the territory of one country, information related to the offer of tourist products and services reaches potential consumers worldwide. This creates greater competition for tourism businesses while offering access to a potentially unlimited market.

Due to its global reach, tourism can be examined from a multipolar perspective. In contrast to the earlier period, when the G7 countries played a dominant role in tourism, the developing BRICS nations can be characterized as emerging powers in this sector. This reflects a trend in which BRICS countries are gaining a prominent position in the World Travel Market (Zhou, 2022). The multipolarity of tourism can also be reflected through its development in smaller areas or under-emphasized locations characterized by different directions of development and contrasts between different cities and businesses on various scales (Kuklina et al., 2017; Shafqat & Byun, 2019). Localized adjusts should not neglect tourists' diversity. Authors Vargas-Calderón et al. (2021) recognized that tourists from different countries exhibit variations in culture and other sociological aspects, which often differs from destinations' characteristics. Such diversity significantly influence perception, preferences, and satisfaction of visitors with the overall travel experience. This necessitates the adaptation of tourism offers to user preferences.

A specialized area of artificial intelligence – recommender systems enable the personalization of content to the tourists' preferences or behavioral patterns. They reduce the time needed to select an appropriate destination or content while minimizing the cognitive effort required to find options aligning with individual preferences. On the other hand, business entities in the tourism sector are improving their efficiency and productivity by targeting individuals or groups with customized offers, allowing them to stay ahead of the competition (Tussyadiah & Miller, 2019). The benefits of recommender systems suggest that they could play a significant role in promoting tourism in the Republic of Srpska. Although beneficial for businesses, their implementation is complex due to challenges, such as cold start, the accuracy of recommendations, efficiency, data sparsity, and others (Solano-Barliza et al., 2024). Natural language processing (NLP) techniques, in particular topic modeling, represent one direction toward addressing these issues. Topic modeling enables the extraction of prevailing topics from texts that can serve as auxiliary data for enriching user profiles, which are further used to build recommendations within recommender systems.

This paper is organized as follows. Section 2 reviews recommender systems in tourism. Section 3 addresses the key development challenges recommender systems in tourism face. Section 4 provides information on topic modeling and available approaches, while Section 5 explores possibilities of overcoming the development challenges of recommender systems by introducing topic modeling.

2. RECOMMENDER SYSTEMS IN TOURISM

Recommender systems can be described as filtering tools that suggest personalized content and information (Roy & Dutta, 2022). They use different data sources to derive user interests (Aggarwal, 2016). There are several types of recommender systems. Collaborative-filtering utilize item ratings from different users that describe their preference. They then leverage the collaborative capabilities of those ratings to find users with similar preferences based on which the recommendations are generated (Aggarwal, 2016). In content-based filtering user profiles are built based on the users' historical interactions with items and users' ratings of items. This type of recommender system compares the user profile attributes with item features to generate recommendations (Lops et al., 2011). Knowledge-based recommender systems do not require user ratings to generate suggestions. Instead, they acquire knowledge about user preferences, which is gathered through interactions with the user by asking questions or other similar methods (Burke, 2000). There are also hybrid recommender systems that use a combination of the aforementioned types to overcome their limitations (Çano & Morisio, 2017).

Recommender systems are applied in a variety of service domains such as educational courses (Lynn & Emanuel, 2021), healthcare (De Croon et al., 2021), financial services (Sharaf et al., 2022), telecomunication (Zhang et al., 2013) and more, among which tourism is one of the most prominent. Tourism recommender systems can offer a wide range of personalized travel services (Sarkar et al., 2023):

- Tourist packages that combine destination localities with associated services (e.g., accommodation and booking options).
- Attraction recommendations with associated close by tourist services.
- Trip plans, where routes are generated based on attractions users are most likely to prefer.

In many cases, users were unaware of these places until the system brought them up in the form of recommendations.

The goal of recommender systems in tourism sector is to match the characteristics of tourist attractions with user preferences, while dynamically refining those preferences based on both implicit and explicit user feedback (Sieg et al., 2007). To achieve this, some systems are enhanced with contextual information about tourist locations, such as weather conditions, time of visit, availability of service, congestion at attraction localities, demographic data, etc., (Abowd et al., 1999). Additional knowledge about tourist preferences can be obtained through integration with social media (Sarkar et al., 2023). This enables recommender systems to collect and analyse user-generated content, such as images, videos, reviews, or comments and use this auxiliary knowledge to enhance personalization of recommendations.

Points of Interest (POIs) are an important feature of these systems, representing locations that are attractive or relevant to the user in some way (Sarkar et al., 2023). POI has two main components, POI attributes and user preference pieces of information. POI attributes consist of two groups of information, tourist's opinions (subjective part) and location information (Katsumi et al., 2020). The recommendations are provided as sequences of POIs, allowing users to decide about the subsequent destinations based on their current location (Massimo & Ricci, 2022).

The advantages of using tourism recommender systems are numerous. They can enhance the quality of tourism services, improve user satisfaction, and their overall experience. Booking accommodation becomes faster and easier, reducing users' cognitive load. Moreover, such systems can promote destinations and increase the number of tourists visiting them. In general, tourists and tourism businesses can benefit from technology through enhanced quality, safety, and efficiency (Solano-Barliza et al., 2024). The most popular web platforms using tourism recommender systems include Booking, TripAdvisor, Airbnb, Trivago, and others.

3. CHALLENGES IN TOURISM RECOMMENDER SYSTEMS

Although recommender systems offer various benefits, their implementation exhibits challenges concerning integration and functioning. The challenges inherent in both recommender systems in tourism and other areas relate to the following challenges.

Accuracy shows how well the recommender system matches its suggestions with user preferences. Higher accuracy means that the system's suggestions are more relevant to the user's preferences (Solano-Barliza et al., 2024). Achieving high accuracy is a primary goal of recommender systems, yet it remains a major challenge. Authors (Sarkar et al., 2023) emphasize that recommendation systems in tourism experience issues with evaluations, as evaluation metrics, such as the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), rely on tourist feedback, which may not capture the quality of recommendations.

The *cold-start* problem arises when a new user interacts with the system for the first time, without any prior ratings, or when a newly introduced destination lacks visitor feedback (Kolahkaj et al., 2020). This problem often appears in collaborative-filtering-based recommender systems.

Sparsity is a problem related to the cold-start issue and most often is associated with collaborative filtering-based recommender systems, where the user-item matrix containing rating data is sparse. This typically occurs when tourists only visit a few locations or do not provide ratings, and when a location is new and lacks ratings resulting in a sparse matrix. Consequently, generating accurate recommendations becomes challenging (Singh, 2020).

Scalability becomes a challenge as the number of locations and tourists increases, requiring more time for computation during the recommendation process (Singh, 2020). Maintaining system efficiency under these conditions is not an easy task. One of the most common approaches to address this issue is dimensionality reduction.

Serendipity refers to the discovery of new and unexpected tourist locations or attractions that the user was previously unaware of. While achieving serendipity can be risky as it may reduce accuracy when done correctly, it can be highly effective (Dareddy, 2016).

Privacy is an important aspect of any information system. The storage and analysis of private tourist information must be secured, ensuring protection against potential breaches and data leaks. Moreover, the identification of individuals without their permission should not be possible (Dareddy, 2016).

Some of the challenges more characteristic to tourism recommender systems than others refer to the following.

Group recommendations can be challenging because the system needs to consider the diverse individual preferences of tourists and provide recommendations for the entire group. Factors such as the number of group members, group characteristics, and individual restrictions are just a few of the many aspects that need to be considered in these systems (Dareddy, 2016).

Changing user preference. Current user preferences may differ from their general or previous preferences. Different attributes of tourist locations can become more important at different times due to the changing nature of tourist needs. Recommender systems must provide specific information based on the specific location and certain time (Hamid et al., 2021).

Tracking tourist behavior on the server side is a challenge when trying to extract preference changes from the client-side collected tourist data (Hamid et al., 2021).

Authors Sarkar et al. (2023) indicate that inefficiency is observed when tourism recommender systems are faced with:

- *Dynamic planning*, which is necessary for adaptation of recommendation of localities in real-time.

- *Mobility of users* where geo-referenced pieces of information are utilized in systems and users are often in interaction with mobile devices. The recommended user interface has to be adequate for mobile device.
- The *integration* of information from various sources, such as restaurants and airlines, can be a challenging task. Standardizing and creating an appropriate format for this information is crucial for ensuring smooth interoperability across systems.

All of these challenges can cause irrelevant recommendations, resulting in a poor user experience. That is the reason why it is crucial to address them to ensure high-quality and accurate recommendations, which in turn can improve the efficiency and profitability of tourism businesses (Solano-Barliza et al., 2024). Researchers are seeking new approaches to addressing them and topic modeling has proven to be effective approach.

4. TOPIC MODELING

Natural Language Processing (NLP) is a set of computational methods for automated analysis of human language and structured representation (Chowdhary, 2020). It is used for various tasks, among which is topic modeling (Chowdhary, 2020). Topic modeling discovers hidden topical patterns of words in a collection of documents (Barde & Bainwad, 2017). Topics are often referred to as latent variables (Vayansky & Kumar, 2020). Topic modeling is often a part of AI-based systems for text searching, summarization, classification, information extraction, automatic language translation, question answering, knowledge acquisition, text generation, and more (Chowdhary, 2020).

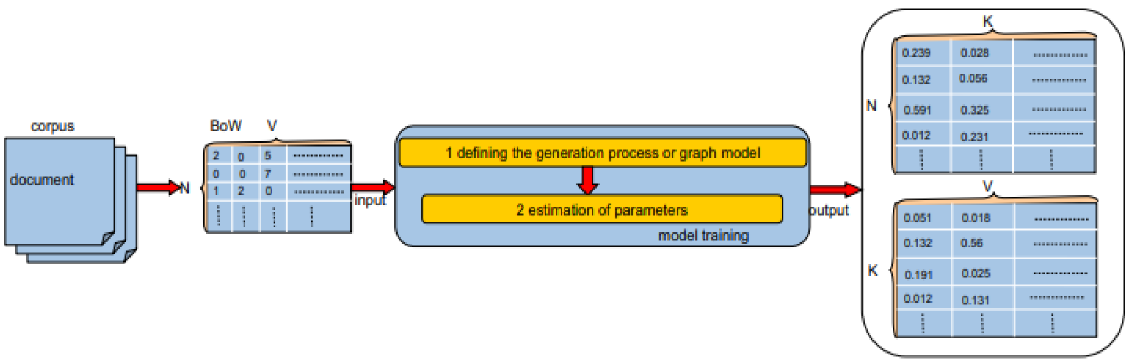
Stages of topic modeling process are presented in Figure 1. The first phase starts with a corpus, which is a collection of text documents. An important step in this phase is document representation, which involves vectorizing the text, such Bag of Words (BoW), Term Frequency - Inverse Document Frequency (TF-IDF), or more sophisticated word embeddings like Word2Vec, GloVe, or BERT. This phase results in document-term matrix – DTM (or term-document matrix), which shows the distribution of words across documents. During this phase, various text pre-processing techniques are commonly applied, including tokenization, lowercasing, stemming, lemmatization, stop word removal, n-grams, and others (L. Liu et al., 2016).

The next phase is model training. The main goal of topic modeling is to discover latent variables (topics) within a corpus of documents. A topic can be described as a probability distribution over a fixed vocabulary. Each discovered topic consists of words with associated probabilities, and each document contains a distribution of topics (L. Liu et al., 2016). For example, a topic labelled “sports” might include high-probability words such as „football“, „basketball“, „player“, „score“, „World Cup“, etc. In topic modeling, documents are assumed to be mixtures of multiple topics. The core task is to infer the distribution of topics within each document as well as the distribution of words within each topic. This is typically achieved by a generative process for documents and estimating the underlying parameters (L. Liu et al., 2016).

The result or output of the two most commonly used topic models, Latent Dirichlet Allocation (LDA) and Probabilistic Latent Semantic Analysis (PLSA), are two matrices (L. Liu et al., 2016):

- document-topic distribution matrix (distribution of topics in documents), and
- topic-word distribution matrix (distribution of words in topics).

Figure 1. Steps in the topic modeling process



Source: (L. Liu et al., 2016)

Authors Abdelrazek et al. (2023) recognized four categories of topic modeling, according to baseline mathematical model: algebraic, fuzzy, probabilistic, and neural. Algebraic topic modeling methods perform DTM decomposition using different mathematical methods, such as Singular Value Decomposition (SVD), and as such they are often used as dimensionality reduction techniques. Fuzzy topic modeling uses clustering techniques. Issues related to sparsity are effectively solved with fuzzy approach (Abdelrazek et al., 2023). Probabilistic topic models are rooted in probability theory, while neural topic models are based on deep learning techniques. In tourism research, most commonly used approach to topic modeling is probabilistic, in particular Latent Dirichlet Allocation (LDA) (Laureate et al., 2023) (Grljević & Marić, 2024).

Latent Dirichlet Allocation (LDA) is a topic modeling algorithm in which multiple topics can be associated with a single document, and the number of topics k must be predefined. Each document in the corpus contains a different proportion of these predefined topics. The topic distribution is learned through statistical inference. Documents are assumed to be mixtures of topics and each word is generated by first sampling a topic and then a word from that topic's distribution (Kherwa & Bansal, 2018).

However, this approach exhibits certain limitations that should be considered when selecting suitable approach to topic modeling. According to Abdelrazek et al.(2023), LDA is simple, intuitive, extensible, and interpretable, while inference becomes complicated with increased model complexity. Although it is prevailing approach to modeling short texts (Laureate et al., 2023), LDA has proven sensitivity on lack of context (Yan et al., 2013), (Tang et al., 2014), (Mazarura & de Waal, 2016), (Luyi Zou & William Wei Song, 2016), (Laureate et al., 2023) and demonstrated suitability for documents longer than 50 words (Vayansky & Kumar, 2020).

5. ADDRESSING TOURISM RECOMMENDER SYSTEM CHALLENGES WITH TOPIC MODELING

Discovering latent topics with topic modeling can help in addressing development challenges in recommender systems. Most commonly, this is achieved by enhancing the input data of the recommender system, where the extracted topics serve as features. The following section presents how various authors have used topic modeling to enhance recommender systems.

Kumar and Hanji (2024) used topic modeling to improve prediction accuracy and extract user preferences in a travel recommender system. Authors used data collected from TripAdvisor. User preferences were extracted using LDA. Correlated Topic Modeling (CTM) was also used to discover relationships among latent topics. Furhermore authors utilized Morphological Linear Neural Network (MLNN) to extract sentiment scores from the textual content. Then these scores were combined with star ratings to generate recommendations. The proposed model was compared to other state-of-the-art models and demonstrated superior performance in terms of accuracy, precision, and recall. The study also emphasized that the polarity of travelers' reviews was at the heart of the research.

Mishra, Urolagin, and Irani (2023) developed a knowledge-based restaurant recommender system. They applied the NMF algorithm to extract latent topics from user reviews, which shows user preferences. These topics were then used as input for the recommender system. While interacting with the system, users were asked about their preferred type of cuisine, or about the city where they would like to visit a restaurant and more. If user is interested in "food", the system will suggest restaurants with the highest positive value for the food-related topic.

Liu (2022) created route recommendation algorithm with LDA topic modeling and matrix decomposition to extract features from social network data. The extracted topics represent user interests and they were used for personalization and to improve the accuracy of the recommendations.

Noorian (2024) developed a hybrid tourism recommender system that utilizes demographic data and context information such as time and location. Topic modeling was used to analyze previous tourist trips and to extract the topic preferences of users and POI locations. These topics are further used to create user-POI and user-user profiles, enabling recommendations based on user similarities. A similar model was used by Noorian and Harounabadi (2023) in their paper. This is especially useful in situations where explicit data is limited or unavailable. This approach improved personalization and addressed issues such as data sparsity and cold-start.

Shafqat and Byun (2019) used topic modeling to recommend under-emphasized tourist destinations. To generate cross-mapping for each of the locations, authors combined sentiment analysis of user reviews, topic modeling over travel blogs to identify topics of interest, and used information, such as weather conditions. The results showed that combining topic modeling with sentiment analysis in the recommender system achieved an accuracy of approximately 94%. Proposed approach can also be helpful in achieving the serendipity of the recommendations.

Rossetti, Stella, and Zanker (2016) built a Topic-Criteria model for extracting user preference topics from user reviews. This information is used for rating of each topic, showing how well tourism business owners perform in different aspects. Test results showed that this approach not only increased accuracy but also improved recommender systems with explanations and transparency.

CONCLUSION

Recommender systems play an important role across various domains. They enable personalized recommendations and enhance user experiences. Tourism is particularly attractive industry sector for their application. The use of recommender systems provides benefits not only to tourists but also to service providers in the tourism industry. However, despite their numerous benefits, implementing recommender systems is not a straightforward task due to challenges such as the cold-start problem, data sparsity, personalization and preference changing, accuracy, serendipity, and other related issues. Topic modeling, as a specific NLP technique, can provide help in addressing these challenges. By extracting latent topics, new possibilities are created for enhancing recommender systems. These latent topics (themes) can serve as additional features that can help to overcome development-related issues. A review of the existing literature has shown that topics are most commonly extracted from user reviews, but also from various posts related to tourist destinations, photo descriptions, general information about tourist locations from multiple platforms and social networks, as well as other forms of textual data. Topic modeling in tourism research is mostly used to discover user preferences, to personalize recommendations, address sparsity problems, provide explanations, and recommend under-emphasized or unpopular destinations. Research findings indicate that integrating topic modeling into recommender systems can significantly improve the accuracy of recommendations. This shows that topic modeling can effectively support the development of recommender systems and provide various benefits through its implementation.

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