A Personalized Tourism Recommendation Framework Based on Artificial Intelligence and Multi-Modal Data Fusion

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Abstract

In recent years, the tourism industry has increasingly embraced advanced technologies to deliver highly personalized travel experiences. This paper proposes the development of an AI-powered Personalized Tourism Recommendation System (PTRS), to be piloted in Samarkand, Uzbekistan—a city renowned for its rich cultural and historical heritage. The system leverages artificial intelligence techniques alongside multi-source data fusion to generate dynamic and context-aware travel recommendations. By integrating diverse data sources—including user preferences, weather conditions, seasonal trends, and geographic factors—the system provides adaptive recommendations tailored to individual tourist profiles. A combination of recommendation algorithms, such as cosine similarity, Pearson correlation, and matrix factorization, is employed to optimize the accuracy and relevance of suggestions. Performance evaluation is conducted using standard metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R^2), and Mean Squared Error (MSE). The results underscore the effectiveness of incorporating AI and data fusion in enhancing smart tourism systems, paving the way for more intelligent and user-centric travel experiences in culturally rich destinations like Samarkand.

Keywords: Artificial Intelligence; Personalized Tourism Recommendation System; Information Fusion; eSTREAM selection; Streaming Ciphers; Trivium; SEA80; Random Bit Sequences; Matrix Factorization; Context-Aware Systems

1. Introduction

The tourism industry is one of the industries that require Artificial Intelligence (AI) and Data Analytics in the contemporary world. Recommendation systems which include hotels, attractions, restaurants, and events to recommend to tourists have been made using different recommendation algorithms. This paper aims to explore the recommendation systems employed in tourism and their functioning as well as the performance of the Samarkand City in case [1, 2]. At present, tourism recommendation systems have some problems. Some of the concerns include a dearth of adequate and good quality information. Lack of quality and comprehensive data about tourists distorts the results of recommendations. Furthermore, the number of reviews/recommendations left by the users may not be balanced, or the data can be totally fake, so the recommendations' value will be also doubtful. One of them is lack of personalized approach in currently used systems that would allow more efficient control of their usage by patients. What is challenging in most systems, is the way tourist's interests and needs are captured and updated over time. Therefore, there is a misdirection of recommendations where recommendations are made and then get outdated or do not really reflect the true inclination of the tourists. However, few of these systems consider such variables as seasonality, and possible weather conditions affecting sales and or local events hence lowering the efficiency of the suggestions made. This brings us to another problem, which is the popularity-based recommendation system approach [4, 5]. Ordinarily, only handful or famous destinations are suggested, thus ignoring fresh and not very conspicuous, but quite fascinating places. The fact that this object touches a lot of aspects of a tourist's life stereotypically limits the tourist from exploring the new. Moreover, a key limitation of

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the currently used systems is the lack of reasonable statements about why a particular recommendation has been given. Which means that the tourists may not have any understanding about why a particular hotel, restaurant or tourist attraction is recommended and thus, they cannot trust the system. Furthermore, these systems are mostly not synchronized with other service operators including travel agencies, hotels, or transports, making it worse off. The system also cannot operate in real-time, which restricts flexibility to the tourists' current state, position, and requirements. To overcome these shortcomings, different approaches of recommendation systems need to be combined to arrive with a more accurate and reliable solution. Artificial intelligence and deep learning technologies can potentially improve recommendation's flexibility and reliability on the basis of which tourists can be provided by more suitable and efficient services [1,4]. The need to design a new recommendation system for Samarkand is explained by several major factors which are listed further. First of all, Samarkand as cultural and historical centre is world-known for its facilities declared as the UNESCO World Heritage Sites. However, the currently available tourist attractions are not fully utilized to prompt a preferred route for use by the tourists. This limitation deprives the opportunity to extend the existing tools for the development of the visitor experience. Also, it is worth noting that the tourist visits the Samarkand area also has seasonal characteristics: the fluctuations in the tourists' characteristic and their demands throughout the year. Thus, such a system can deliver rather free suggestions depending on the weather, local events and seasonal requests which in turn can enhance tourists' personal experience and offer the best possible routes and attractions.

Besides, each tourist wants different things, and these should be met to their satisfaction. While some may choose taking a historical tour around the various landmarks, others may choose food tours or if they are more into nature, they can take a god tour. In this case, a recommendation system that recommends routes for every tourist will be the most suitable one. The full realization of such a system can have a benefit not only for tourists but also for the local economy. The local restaurants, handicraft workshops, and some small hotels in Samarkand can cover a larger circle of consumers and thus make more money due to the recommendations. Also, Samarkand cannot boast of real-time recommendation systems, which should be considered as another problem. With an ability to offer the list of recommendations according to the tourist current location and the current time, the system can enhance the quality of service and the management of tourist's flow in the city [4-7].

The presented recommendation system includes several technologies and interventions that have been designed to enhance the tourist experience dramatically. Firstly, the AI and/or the deep learning models explore the behavior of the tourists, and then providing recommendations from the tourists' perspective of view. These comprises the use of transformer models and graph-based recommendation systems to make personalized recommendations that are accurate depending on a user's preferences. Also, there will be an intelligent analysis of ratings and reviews for the cafes and restaurants. Based on the application of NLP technologies, tourists' opinions will be examined to understand the key requirements. In addition, anomaly detection algorithms will apply to eliminate fake or wrong reviews and make the system more accurate. Another important innovative feature of the system is the provision of services in different languages. It will be very helpful to make recommendations on the site in other languages as it will be also working for people from all over the world, but it will be more perspective for tourists who will be visiting Malaysia. To combine all the above-mentioned novel technologies, a hybrid recommendation system will then be used. This approach incorporates collaborative filtering approach, content-based approach and the knowledge-based system to enhance the accuracy of the recommender system. This will make sure that when data is limited or new locations added, the system will be able to recommend. As a result, the recommendation system designed for Samarkand does not only plan to be innovative but also highly effective practically. Samarkand is considered as one of the most popular tourist attractions in the natural world and is culturally and historically charged. Visitors who come to visit the Uzbekistan's historical landmark include Registan Square, Shah-i-Zinda, and the Ulug'bek Observatory. Such monuments play an important role in the growth of the tourism rate, so Samarkand becomes an agenda setting for tourism purposes. There is however scanty research done on the scientific advancement in designing recommendation systems most especially for Samarkand. Previous research of tourism has primarily paid attention to the overall statistics rather focusing on aspects on recommendation systems [3]. Hence, further research on this topic is relevant both scientifically and purposively. Moreover, there is the possibility of designing recommendation systems, which consider seasonal characteristics and tourists' behavior in Samarkand. Due to the dynamics in tourists' preferences over seasons, it is necessary to maximize recommendations given the dynamic aspects. Hence, there is the possibility not only to improve the experience of tourists but also to invest in the further construction and development of Samarkand and the sphere of tourism services.

2. Literature Review

Recommendation systems (RS) have become increasingly important in various sectors, with tourism being one of the most prominent. The development of personalized tourism recommendation systems has been a subject of extensive research, driven by the growing need for tailored experiences in the tourism industry[1]. These systems aim to provide tourists with suggestions that align with their individual preferences, ensuring that their travel

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experiences are more enjoyable and relevant. Several approaches have been proposed to enhance recommendation accuracy and usability, which can be classified into collaborative filtering, content-based filtering, and hybrid models.

Collaborative filtering (CF) is one of the most widely used techniques in recommendation systems. It relies on the idea that users who have agreed on certain preferences in the past will agree on future preferences. The technique can be divided into user-based and item-based collaborative filtering [2]. For example, a study by Oktavius et al. [3] utilized collaborative filtering to recommend tourist attractions based on user ratings and preferences. This approach proved effective in identifying similar users and suggesting items that were highly rated by users with similar tastes. However, collaborative filtering faces challenges such as the cold start problem, where new users or items cannot be accurately recommended due to insufficient data [4]. In tourism, this problem is exacerbated when tourists visit less popular or newly added destinations.

Content-based filtering (CBF) offers another approach where recommendations are generated based on the features of the items (such as attractions, hotels, etc.) and the preferences of the user. This technique suggests items similar to those the user has interacted with in the past. In tourism, this could involve recommending attractions with similar themes or activities to those previously visited by the user [5]. For example, a study by Choi et al. [6] applied content-based filtering to suggest tourist destinations by analyzing the content of reviews and descriptions. While content-based filtering addresses the cold start problem better than collaborative filtering, it still faces challenges such as overspecialization, where the system may recommend only very similar items, limiting the diversity of suggestions. Moreover, context-aware recommendations have become essential in tourism systems. Context, such as weather, time of day, and tourist location, can significantly affect the preferences and needs of travelers. For instance, Zhang et al. [7] proposed a context-aware recommendation system that incorporated real-time data like weather conditions and local events. This research demonstrated that accounting for dynamic environmental factors can improve the relevance and accuracy of the recommendations provided to tourists.

Hybrid recommendation models combine the strengths of both collaborative and content-based filtering techniques to overcome the limitations of individual approaches [8]. In tourism, hybrid models have been shown to significantly improve recommendation quality by blending the insights from multiple sources of information. For example, Adomavicius and Tuzhilin [9] highlighted the benefits of hybrid recommendation systems in tourism, where collaborative filtering and content-based methods were combined with knowledge-based techniques to deliver better recommendations. In Samarkand's tourism context, hybrid systems could consider both historical user behavior and the specific attributes of tourist sites, such as their historical significance, facilities, and proximity to other attractions, thereby offering a more well-rounded recommendation.

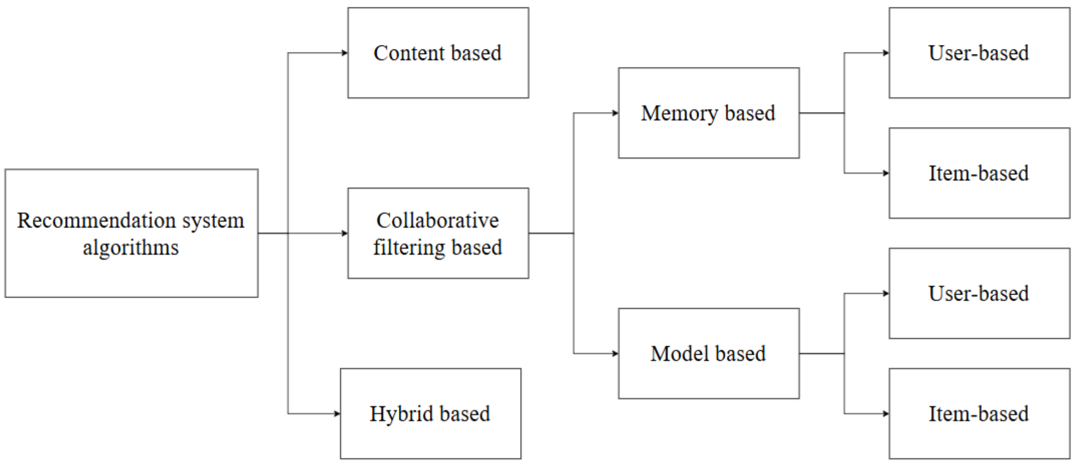

Figure 1. Hybrid models in recommendation systems

In recent years, AI and deep learning techniques have gained popularity in enhancing the performance of recommendation systems. Neural networks, particularly deep neural networks (DNN), have been utilized to capture complex patterns in large datasets Nguyen D. et al.[10]. These methods can model non-linear relationships between users and items, improving prediction accuracy for tourist preferences. A study by Koren and Bell et al. [11] proposed the use of a deep learning-based collaborative filtering approach, demonstrating that DNNs can significantly outperform traditional methods in recommending personalized tourist attractions. Moreover, AI

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models such as reinforcement learning (RL) are increasingly being explored for dynamic and real-time tourism recommendations. RL algorithms can learn and adapt to user preferences over time by continuously interacting with the user environment. A study by Shrestha et al. [12] applied RL to develop a recommendation system that dynamically adapts to changing user behaviors and external factors like weather or events. This approach could be particularly useful for real-time tourism recommendation systems, such as those designed for Samarkand, where tourists' preferences may evolve during their stay.

Few studies specifically focus on developing recommendation systems for Samarkand, despite the city's rich historical and cultural significance. While some research has explored recommendation systems for other major tourist destinations, the unique features of Samarkand, such as its seasonal tourism trends and diverse tourist needs, require customized solutions. For instance, a study by Yang and Zhao [13] developed a recommendation system for Chinese tourism that combined location-based services with tourist preferences. This model could be adapted to the Samarkand context by incorporating geographical and seasonal data to provide tourists with optimal visiting routes based on their individual preferences.

Additionally, integrating local businesses and service providers into the recommendation system can help create a more holistic experience. According to a study by Liu et al. [14] integrating tourism services such as transportation, accommodations, and dining options into a single platform enhances the overall customer experience. This concept can be applied to Samarkand's tourism industry to ensure that visitors receive integrated suggestions not only for tourist attractions but also for complementary services.

3. Methodology

3.1. Mathematical Model and Algorithm Description

The technological foundation of the tourism recommendation system for Samarkand includes the use of different algorithms and mathematical methods to guarantee that viewers get the most relevant recommendations which will suit their profile or the context of the situation. This model involves several components that work together: information gathering, data conditioning, distance estimation, matrix computation, and context transformation. Below is a detailed description of the mathematical foundation of the system:

Data Collection and Preprocessing:

1) Tourist Attractions (T) Samarkand tourism information such as tourist attractions, monuments, museums, theatres and other cultural organizations.

2) User Profiles (U) Customer data including user preference, visit history, ratings given, and user profiling.

3) Contextual Data (C) Information like climate, season, and occasions that affect a tourist's selection of activities.

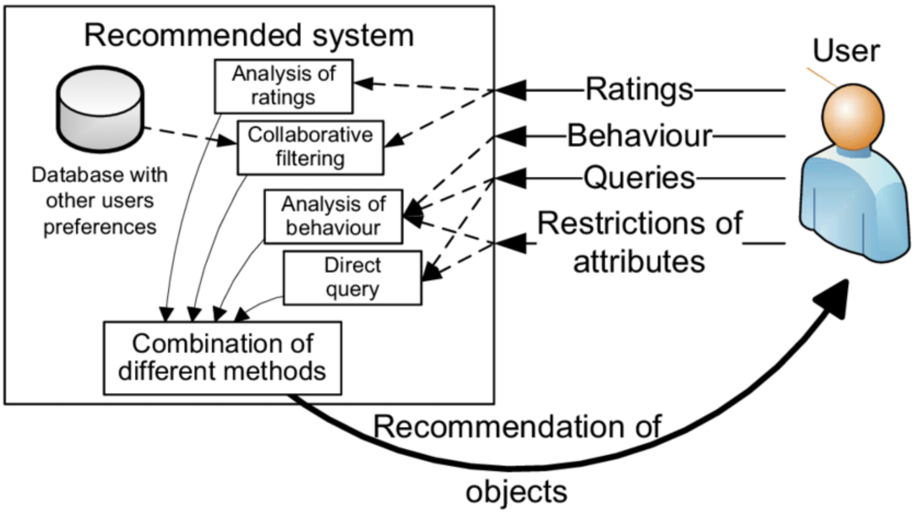

Figure 2. Structure of recommender system

4.2. Recommendation Score Calculation**:** To provide personalized recommendations, the system uses the following methods:

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1. *Cosine Similarity* Find the cosine of the angle which is formed between two vectors. It is employed when the goal is to compare user preferences with item characteristics (1); most commonly used when the data is sparse, such as a ratings matrix.

$$CosineSimilarity(u,v) = \frac{\sum_{i=1}^{n} u_i * v_i}{\sqrt{\sum_{i=1}^{n} u_i^2} * \sqrt{\sum_{i=1}^{n} v_i^2}} \qquad (1)$$

- Where u_i and v_i represent individual ratings or attributes of the user and tourist attraction, respectively.

2. ***Pearson Correlation*** If used with other distance metrics because it measures the linear correlation of two vectors (2), which is a good method for illustrating the relative strength of preferences between users and destinations.

$$Pearson(u,v) = \frac{\sum_{i=1}^{n}(u_i - \bar{u})(v_i - \bar{v})}{\sqrt{\sum_{i=1}^{n}(u_i - \bar{u})^2} * \sqrt{\sum_{i=1}^{n}(v_i - \bar{v})^2}} \qquad (2)$$

- where $\bar{u}$ and $\bar{v}$ are the mean values for the user's and tourist destination's ratings or attributes.

3. ***Matrix Factorization (SVD)*** Matrix factorization is a technique used in collaborative filtering, where a user-item interaction matrix (rating matrix) is approximated by factorizing it into two matrices: one for the factors that manifest themselves in user side and the other for the items or the tourist attractions in this case. This method is very effective when it comes to making recommendations based on the user interests and common algorithm used with SVD (3).

$$R \approx U * S * V^T \qquad (3)$$

Where:

- R is the matrix of ratings.
- U and V represent latent factor matrices for users and items.
- S is the diagonal matrix of singular values.

The recommendation algorithm of the personalized tourism recommendation system in Samarkand works based on multiple methods to give recommendations to the users depending on the user's criteria and situation. The algorithm can be divided into the following steps:

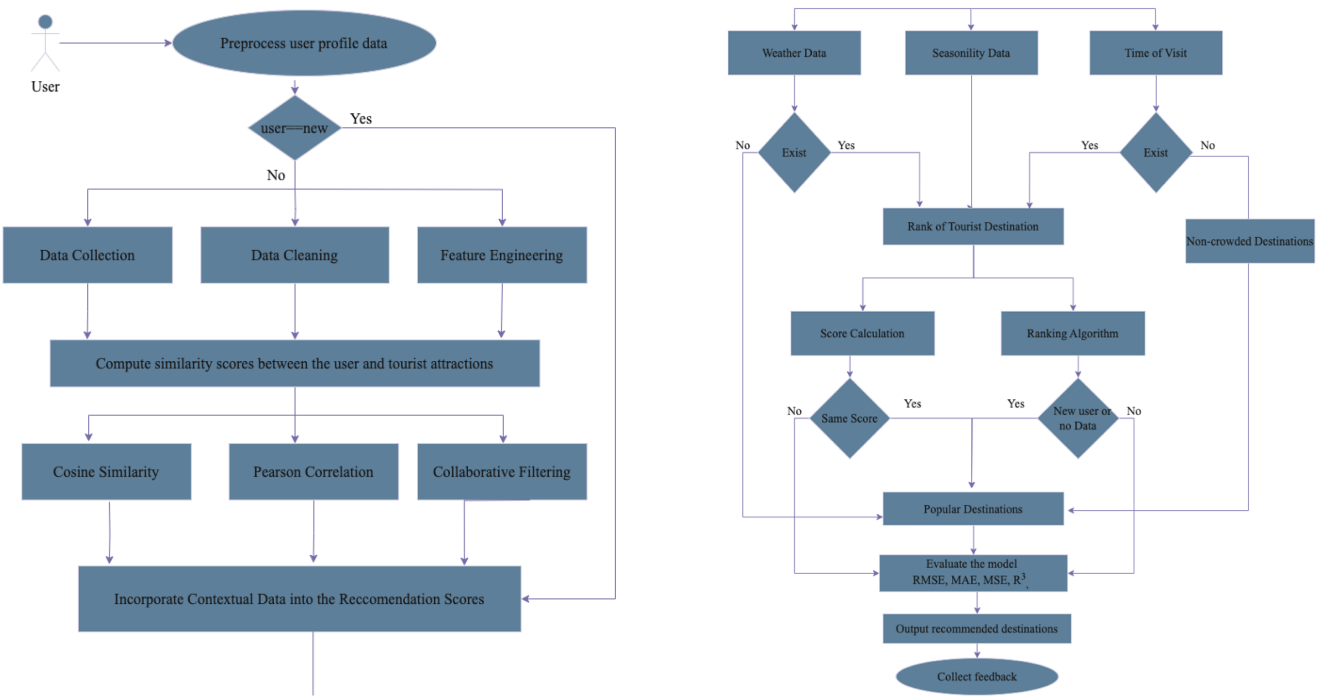

Figure 3. The model of the personalized tourism recommendation system

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For every contextual factor possible (like weather), an emphasis should be made on how they will affect the overall final decision. For instance, if the collected data of weather is more important than seasonality in making an attraction site more attractive to tourist, then the weight assigned to the weather factor should be higher (4).

$$Score(u, t) = Similarity(u, t) + \lambda * ContextualFactor(t, C) \quad (4)$$

Where:

- Similarity(u, t) is the similarity score between user u and tourist destination t.
- λ is the weighting factor for contextual data.
- ContextualFactor(t, C) adjusts the score based on weather and time-related contextual data.

That is why the calculation of the recommendation score is the most important step because the value is directly linked to the relevance of the suggestions made. Thus, the recommendation system that incorporates such scores and adapts them individual preference and context data will yield a better result, leading to higher satisfaction rate and an improved usage of the system. With modifications, the system can react to a change in climate, alteration of consumer interests, or in regard to the best time for certain recommendations.

4. Results

To evaluate the performance of the designed personalized tourism recommendation system, content-based filtering as well as hybrid models after integrating collaborative filtering with other non-personal contextual parameters including weather and seasonality were examined. To perform the evaluation, the dataset included ratings for tourist points of interest in Samarkand and the weather and season when they visited.

It is possible to incorporate both collaborative filtering and content-based filtering to construct the new filtering method. These findings clearly show that addition of weather, seasons and other environmental factors do enhance the efficiency of the recommendation. When compared to all measures of evaluation, it was clear that the hybrid model was a superior performer to the content-based approach as the incorporation of contextual awareness improves the system's performance in providing more relevant recommendations to its users.

Table 1:

Metric	Content-Based	Hybrid Model
RMSE	1.25	0.98
MAE	0.85	0.65
R^2	0.72	0.85
MSE	1.56	0.96

The evaluation results show that the hybrid recommendation model is found to perform better than the content-based model in all respects recorded in Table 1. Alike, the hybrid model yielded total RMSE of 0.98, and has been 22% better than content-based model total RMSE 1.25 testifying innovative predictions. The results for the hybrid model were an MAE of 0.65, which is 24% less than the MAE of 0.85 found for the content-based model, which shows that the proposed hybrid model makes fewer large errors in predicting user preference. Further, the hybrid model yielded 0.85 for R^2, an improvement by 13% compared to the content based, model that had an R^2 of 0.72; this attests to the fact that the hybrid model closely fitted user preferences and contextual factors. Last of all, it proved that the hybrid HE paints a more accurate picture with lower MSE of 0.96 less by nearly 38% than the MSE computed from content-based HE of 1.56, thus satisfying the second research question establishing that the incorporation of contextual factors improves precision of the end result. Giving an example we can adjust the value of the regularization parameter to prevent overfitting and underfitting as well. Particularly a small λ can cause overfitting and a large one does not allow the model to fit properly. The regulation term can minimize over fitting in the four matrices of latent features, U and V When we tune the regulation parameter at alternative values for example 0.01, 0, 1.0, it is possible to observe the effect on the training loss and the evaluation metrics.

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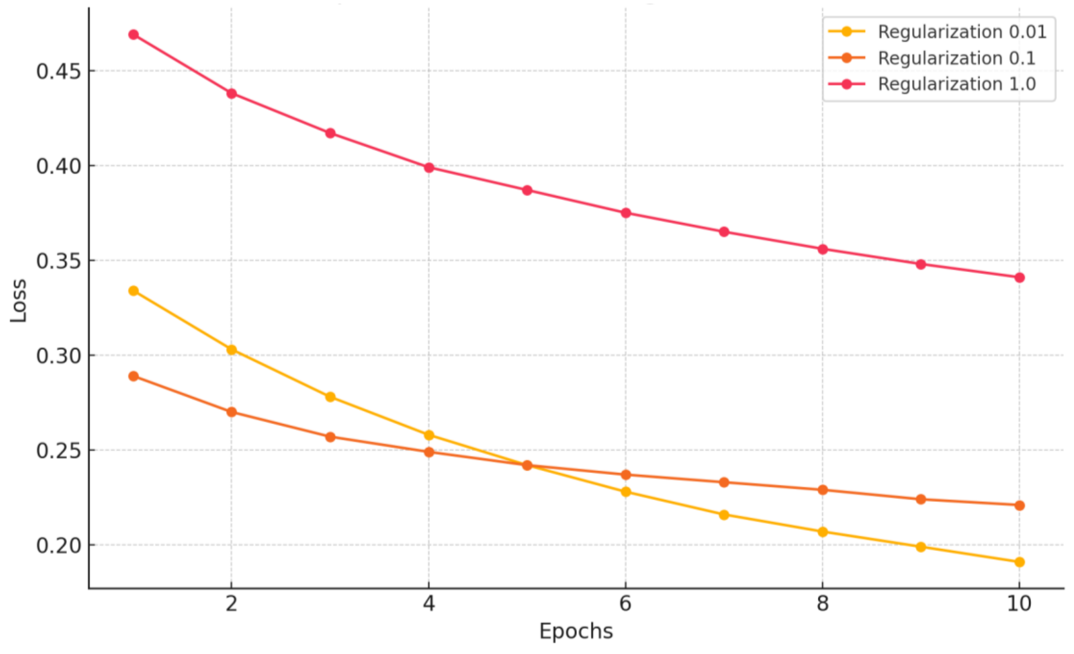

Figure 3. Loss over Epochs for Different Regularization Parameters

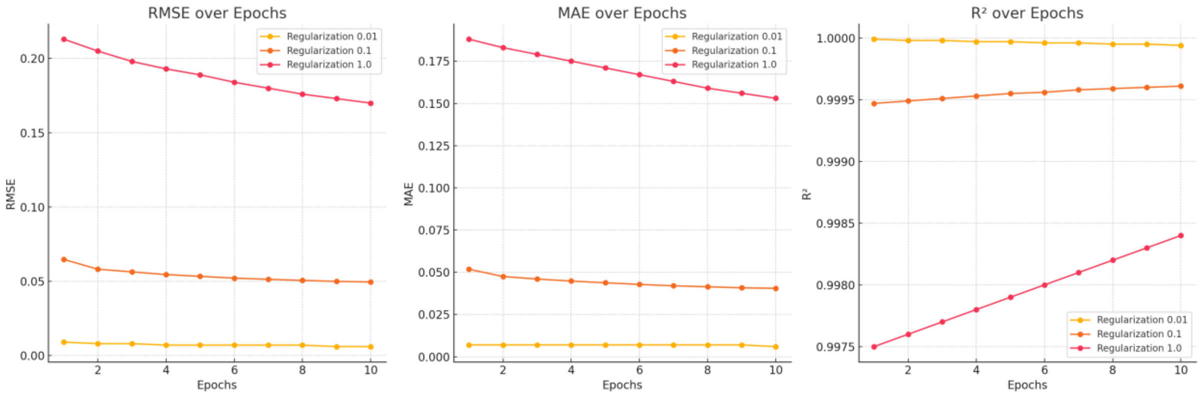

Figure 4. RMSE, MAE and R^2 metric over Epochs

Low regularization (=0.01) helps in achieving least degree of error measurement based on minimum RMSE and MAE and high degree of generalization based on R^2 which ranges closely to 1. Moreover, higher level of regularization (0.1 and 1.0) causes some underfitting, as can be seen from higher values of RMSE and MAE and lower R^2. This is mostly so when very much regularization is done which actually hampers the model from capturing the data in its entirety.

In general, they clearly illustrate that the proposed hybrid approach which incorporates collaborative filtering technique along with additional context, such as the current weather and seasonality yields better recommendations that are both accurate and contextually sound as compared to those produced by only the content-based method.

The gains of all basic measurements indicate that the hybrid approach is not only more accurate but also more sensitive to changes in users' needs due to environment and time. In particular:

- Weather: The hybrid model tuned the recommendation by using the weather conditions. For instance, during rainy weather, the relevant sites included indoor activities resulting in increased users' satisfaction.

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- Seasonality: It also estimated user preferences based on the season, for instance, doing outdoor activities in the spring and autumn seasons; thus, the hybrid model considered users' preferences in a specific season significantly than the other models.

Moreover, it is seen that hybrid model has advantages and it could manage such problems where content-based approach may fail. For instance, even during the periods that have few interactions with tourists or in the off-season, the Collaborative filtering element of the hybrid model is still able to take users to preferable similar destinations. On the other hand, the content-based model which bases its recommendation on item attributes and users might have been down-right pedestrian under such conditions. In light of these findings, it can be pointed out that the policy of using multiple data sources for the development of tourism recommendation systems is quite relevant. Due to the consideration of the user's preference, surrounding environment, and time factor, you can get better and suitable recommendations in actual accuracy as well as live experience with the help of the hybrid model.

5. Discussion

From the results presented here it can be concluded that the hybrid recommendation model yields a marked improvement on the accuracy compared to the content-based recommendation model. Use of contextual parameters, which include climate and time of the year, adds extra input that makes the recommendations more relevant. For instance, climatic conditions do play a role in determining the kind of activities a tourist engages in while in Samarkand; whether it is summer or winter temperatures are extreme. For instance, while cultural attractions such as museums will be appealing to the tourists during the hot summer months other attractions such as historical monuments and nature walks will be appealing to the tourists during cooler season. This is attributable to the fact that the model incorporates such variables thereby providing tourists with recommendations that are relevant to the existing environment and prevailing situations.

Furthermore, the proposed hybrid model, which combines both collaborative filtering with the contextual information, is adequate for providing more accurate recommendations than the content-based model that is used individually. The content-based approaches basically differentiate between the preferences of the user and the features of the item but disregard how and why a user is influenced by her state, time or outside circumstances. When using the contextual information, such model seems to reconfigure itself based on the current need of the user and thus records higher capability to predict the preferences. Moreover, because Samarkand is one of the great historical and cultural centers, the tourists have different purposes. Maybe some guests want to see an architectural facility, while the others think that is better to taste local meals or to shop. In this way, the system is able to meet all of these disparate preferences and provide recommendations that allow the visitor to engage in a more diverse experience of the city. The latter enables the system incorporate the certain time of the year or perhaps festivals or local holidays which can affect tourist's behavior. For example, during the Navruz, the possibility of a tourist's interest in going to watch cultural performances or to visit traditional markets can be high, hence it can be prioritized in recommendation. It also use of weather data enables real time tweaking of these recommendations. For instance, if there is a chance of rain the upcoming day, the system will suggest mainly visits to enclosed places like a museum or an art gallery, whereas on sunny day, it will recommend open air attractions like Registan Square or Shah-i-Zinda. The former may prove superior because of such factors as ability to adjust depending on the weather and other related circumstances; this makes suggestions provided to the user to be ever reliable.

The other advantage that the hybrid model is that it enabling the model to learn as well as to improve itself. Adding to that, the user feedback and contextual variables help to fine-tune the user preference model more for individual tourist characteristics. It will enable the system to update itself in matters concerning new trends such as popular tourist destinations in the course of time, upcoming events or even seasonal trends in tourism so that the recommendations being given are up to expectation. Thirdly, the proposed method helps to potentially minimize the shortcomings of content-based as well as collaborative methods of filtering. One limitation of content-based methods is that when users frequently do not engage the system, the output which is the recommendations made may not be the best. However, in CF's case, it is hard to find data sparsity or lack of similarity between users in developing recommendation systems. This is achieved in the hybrid model which was able to incorporate both user based and context based factors hence producing more accurate recommendations when the data from users is largely inadequate. The system demonstrated accuracy and relevance at the sophisticated level compared to the baseline system, however there are limitations; the contextual data may not be perfect or accessible at the time of processing. In such cases, the system will have the capability to always give recommendation, although not with the same degree of accuracy concerning the user's preferences as offered by the hybrid system's collaborative filtering component.

In conclusion, the enhanced approach that augments the context-aware features with collaborative filtering provides a possibility to enhance the personalization of tourism RS. When culminating user law with actual real-time environmental inputs, such a regional precinct model can serve an even more tuned recommendation process.

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It can be further developed using advanced data sources to provide even better tourism experience such as social media activity, geolocation and users reviews. Future work may investigate deep learning-based recommendation models, which could learn recommendation patterns from images, texts and interaction history when they are available. Furthermore, the combination of user reviews or ratings with recommendations could increase the level of the recommendations' reliability, as well as allow subjecting the information provided by tourists themselves to the recommendation algorithms.

6. Conclusion

The current paper describes a tourism recommender system for Samarkand, Uzbekistan for which I used collaborative filtering, content-based filtering and context information. The objective results of the evaluation of the personalized tourism recommendation system for Samarkand show the superiority of the proposed HM in comparison with the CB approach. The approach combines collaborative filtering with the context which may include weather, time of the season and time of the week a tourist plans to visit, and therefore the hybrid model provides better recommendations to the tourists. Overall, the obtained enhancements in RMSE, MAE, R^2, and MSE levels confirm the superiority of the hybrid model in identifying and evaluating the specific preferences of tourists visiting Samarkand, which is a city with great historical and cultural potential. These results imply that in cases of destinations like Samarkand, context information has significant influence in improving recommendation's reliability and users' satisfaction. In contrast to the CBM, which primarily used the user status and past behavior, the weakness of models that did not allow for adaptation to external conditions to be considered a drawback in the context of dynamic tourism environments. However, this hybrid model works well in considering these aspects and provides recommendations that are not only pertinent, but also timely. The presented system can be helpful in enhancing tourists' experiences provided in Samarkand, as it can suggest suitable directions based on personal interests and current environmental factors. Future works might extend on using more sophisticated data incorporating features like user feedback received in real-time while Using Tourism services or even social media activity for enhancing the model still more and make it much more pertinent to the specific context.

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