ТУРИЗМ

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JOURNEY THROUGH CENTRAL ASIA: DEVELOPING A SPARSE GEO-SOCIAL LOCATION-BASED AND PREFERENCE-AWARE RECOMMENDER SYSTEMS

Abstract. *The rapid growth of location-based services (LBS) has resulted in an increasing demand for personalized and context-aware recommendations. This study aims to develop a sparse geo- social location-based and preference-aware recommender system to provide accurate and relevant suggestions for users in remote areas of Central Asia. We propose a novel framework that integrates geographical, social, and preference information to address the challenges of data sparsity and user mobility in these regions. The proposed model is evaluated through extensive experiments on real- world datasets, demonstrating its effectiveness in improving recommendation quality. Furthermore, the research highlights the potential applications of the proposed system in promoting sustainable tourism, preserving cultural heritage, and fostering social cohesion in Central Asia.*

Keywords: *Location based services, Recommender models, Central Asia, sustainable, tourism.*

Introduction

Preservation of natural resources in Central Asia, characterized by unique landscapes and ecosystems with high biodiversity, necessitates the prioritization of resource protection through responsible tourism practices in the emerging field of sustainable eco-tourism. To ensure economic benefits from tourism activities and preservation efforts, community involvement becomes integral in all aspects of eco-tourism development in Central Asia. Considering the remoteness of certain areas, infrastructure development becomes crucial to cater to the needs of tourists while minimizing environmental degradation [1, 53 p.]. Implementing water supply systems and waste management facilities are examples of such developments. Capacity building and education play significant roles in maintaining ecological balance and enriching guest experiences in nature conservation. Training programs for local guides, tour operators, and hospitality staff focusing on sustainability practices and indigenous knowledge contribute to this aspect. In line with reducing carbon emissions, alternative energy sources like solar or wind power should be considered within eco-tourism models rather than relying solely on fossil fuels, further emphasizing the integration of

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emerging technologies [1, 45 p.]. Developing a sustainable eco- tourism model for Central Asia, which is very remote, requires careful consideration of various factors that impact the region's environment and socio-economic conditions using location aware recommendation system models. Location-aware recommendation models can play a pivotal role in promoting sustainable tourism in Central Asia. The development of sustainable eco-tourism in this region involves identifying the target audience through surveys and data analysis of previous visitors. To understand the preferences of this audience, market research can be conducted using focus groups and surveys. Geographic Information System (GIS) technology can then be utilized to analyze potential eco-tourism locations, taking into account factors such as environmental impact, accessibility, cultural significance, and economic feasibility [2, 80 p.]. Collaboration with local communities and businesses is essential for creating sustainable tourism packages that benefit both visitors and locals. Furthermore, responsible travel practices should be encouraged by educating visitors about their environmental impact and promoting action like waste reduction and energy conservation. Monitoring success metrics, including tracking visitor numbers and gathering feedback, allows for the assessment of eco-tourism effectiveness. Research conducted across various regions in Central Asia, such as Kazakhstan and Uzbekistan, has revealed traveler preferences, including a strong interest in eco-tourism destinations with rich biodiversity, like mountain ranges and natural reserves [1, 30 p.]. Travelers also express a desire to experience the region's unique traditional cuisine and engage in outdoor activities such as trekking and camping. By employing GIS modelling techniques, specific areas with the highest potential for eco-tourism development and minimal environmental impact, such as Altyn Emel National Park and Kolsai Lakes National Park, can be identified. To promote responsible tourism practices, it is recommended to establish partnerships with local communities and businesses in these areas, providing training programs for local guides and creating employment opportunities that improve the economic conditions of residents while preserving their cultural heritage. Implementing these practices can transform Central Asian countries into popular eco-tourism destinations that not only generate revenue but also contribute significantly to environmental conservation efforts [3, 56 p.]. The integration of location-aware recommendation models can enhance the visitor experience by providing personalized and relevant recommendations, guiding tourists towards sustainable attractions and activities that align with their interests and promote responsible tourism practices. Location-aware recommendation systems are recommender systems that utilize location information, such as from mobile devices, in algorithms to deliver more relevant recommendations to users. These systems consider a user's location as context, enabling them to provide recommendations for various points of interest, such as restaurants, museums, and more. In the context of mobile computing scenarios, a comprehensive survey has been conducted to explore location-aware recommendation systems and their main applications across different recommendation domains [2, 13 p.]. The survey provides an overview of the current state-of-the-art in this field and identifies potential avenues for future research. One notable location-aware recommender system is LARS, which incorporates location-based ratings to generate personalized recommendations. This system considers both the user's current location and the ratings assigned to nearby locations, resulting in tailored recommendations that align with the user's preferences. By leveraging the power of location data, LARS aims to alleviate the burden of users having to manually search for engaging and relevant places. The rapid expansion of mobile technology and LBS has created new opportunities for users to explore and interact with their surroundings [4, 96 p.]. Recommender systems have become essential tools for providing personalized and context-aware suggestions based on users' preferences, location, and social connections. However, existing approaches often struggle to cope with the challenges of data sparsity and user mobility in remote areas, such as Central Asia. This study aims to address these issues by proposing a novel framework that integrates geographical, social, and preference information to develop a sparse geo-social location-based and preference-aware recommender system. Location- aware recommendation systems have gained significant attention in recent years due to their ability to provide personalized and contextually relevant recommendations to users. These systems take into consideration various factors to generate recommendations that align with the user's preferences and current situation. This article explores the key factors considered by location-aware recommendation systems, including the user's current location, preferences, time of day, weather conditions, traffic, and social influence. By incorporating these factors into the recommendation algorithms, these systems offer a more tailored and engaging user experience, suggesting nearby places of interest based on the user's location, recommending activities suitable for the time of day and weather conditions, and considering traffic constraints [3, 70 p].

Methodology for identifying location-based service in Kazakhstan

Existing studies on location-based recommender systems primarily focus on densely populated urban areas, where abundant data is readily available. However, research on remote areas, such as Central Asia, is limited. Some studies have attempted to incorporate geographical and social information into recommender systems, but they often fail to consider user preferences and mobility patterns [5, 112 p.]. This study aims to fill this gap by proposing a comprehensive framework that combines these factors to improve recommendation quality in remote regions. To identify location-based services in Kazakhstan, we will use a mixed- methods approach that combines both quantitative and qualitative data. Firstly, we will conduct a survey to understand user preferences and mobility patterns in remote areas of Central Asia. This will be followed by collecting geographical data such as points of interest (POIs) from online sources like Google Maps or Foursquare. We will then develop an algorithm that considers both the user's preferences and POI attributes to recommend locations of interest to users. Finally, we will evaluate the system's effectiveness using metrics such as precision, recall, and F1-score to ensure accurate recommendations for users in remote areas with limited data availability. To develop a personalized location-based service in Kazakhstan, a comprehensive approach can be adopted to collect user data. The collection process should adhere to GDPR regulations and prioritize user consent. A combination of qualitative and quantitative methods can be utilized to gather demographic information, preferences, and other relevant data. One approach involves conducting voluntary surveys that include questions about age, gender, occupation, and user preferences. These surveys should clearly outline the purpose of data collection and provide consent forms to ensure user privacy and compliance with GDPR regulations. By implementing these surveys, valuable qualitative data can be obtained, enabling a deeper understanding of users' needs and preferences. Additionally, focus group sessions can be organized to facilitate more in-depth discussions and gather qualitative insights. These sessions can provide valuable feedback and suggestions directly from users, helping to shape the personalized location-based service to better meet their requirements. To complement the qualitative approach, quantitative methods can also be employed. This can involve partnering with local business directories and leveraging their customer insights. By collaborating with these directories, access to demographic information and user preferences can be obtained. Such quantitative data provides a broader perspective and complements the qualitative data gathered through surveys and focus groups. By combining these qualitative and quantitative methods, a comprehensive dataset can be built to develop a personalized location-based service in Kazakhstan. The collected user data will enable the service to deliver tailored recommendations and enhance the overall user experience. It is important to ensure that all data collection and handling processes are conducted in accordance with GDPR regulations to protect user privacy and maintain data security. To gather comprehensive location data, a combination of approaches can be employed while ensuring compliance with privacy laws. Government databases can serve as valuable sources of information. By accessing these databases, relevant location-based data can be obtained, such as geographical boundaries, points of interest, and public services. It is essential to ensure that all data collection procedures align with privacy regulations to safeguard user information [3, 75 p.]. In addition to government databases, crowd-sourcing mechanisms like OpenStreetMap (OSM) can be leveraged to gather real- time updates about businesses' attributes. OSM is a collaborative mapping platform where users can contribute and update information about various locations. By encouraging user participation, the platform can provide valuable insights into businesses' attributes, including opening hours and popularity. This dynamic and crowdsourced data can enhance the accuracy and currency of the location-based service. While utilizing crowd-sourced data, it is crucial to establish mechanisms to validate and verify the contributed information. Implementing quality control measures and moderation processes can help ensure the reliability and integrity of the data obtained from crowd- sourcing platforms. By combining data from government databases with crowd-sourced information from platforms like OpenStreetMap, a comprehensive dataset can be created for the personalized location-based service. This rich and up-to-date data will enable the service to provide accurate and relevant recommendations to users. It is essential to prioritize privacy and adhere to relevant privacy laws and regulations to protect user information throughout the data collection process. To obtain mobility data for the development of a location-based service, partnerships can be established with mobile app providers that prioritize the protection of personal information privacy rights. These app providers should adhere to strict legal measures and industry standards to ensure the anonymization of GPS traces. Through these partnerships, users of the mobile apps can voluntarily contribute their anonymized GPS traces. It is essential to clearly communicate the purpose of data collection and assure users that their personal information will be protected. Providing incentives or promotions for users who contribute their data can encourage participation and enhance the dataset's richness. Strict legal measures should be in place to safeguard personal information and ensure compliance with privacy regulations. Implementing anonymization techniques to remove personally identifiable information from the collected GPS traces [6, 75 p.]. By anonymizing the data, individual identities are protected, and privacy concerns are addressed. Partnerships with mobile app providers offer an opportunity to gather large- scale and real-time mobility data. This data can provide valuable insights into user behavior, movement patterns, and preferences. Analyzing this anonymized GPS trace data can help in developing a robust location-based service that offers personalized recommendations and enhances the overall user experience. Throughout the data collection process, it is crucial to maintain transparency, adhere to privacy regulations, and respect users' privacy rights. By following these principles, the location-based service can leverage mobility data effectively while prioritizing user privacy and data protection. In order to perform Social Network Analysis (SNA) for the development of a location-based service, APIs provided by social media networks like VKontakte or Facebook can be utilized. These APIs should adhere to privacy policies and regulations to ensure the protection of users' personal information. By leveraging these APIs, it is possible to access data on friends/follower connections and interests across multiple sources. The

API integration should strictly adhere to privacy policies to safeguard users' data and privacy rights. It is crucial to handle the data in compliance with the terms and conditions set by the social media networks, ensuring that user consent is obtained for accessing and analyzing their social network data. SNA techniques can be applied to the collected data to uncover patterns and relationships among users' connections and interests. This analysis can provide valuable insights into the social connections and preferences of users, enabling the development of a more personalized location-based service. Throughout the process, it is essential to prioritize privacy and data protection. The data obtained through the APIs should be handled securely and in accordance with privacy regulations. Anonymization techniques can be applied to ensure that individual identities are protected while still providing valuable insights for analysis. By implementing SNA techniques using APIs provided by social media networks and adhering to privacy policies, the location-based service can gain a deeper understanding of users' social connections and interests. This knowledge can contribute to the development of more accurate and relevant recommendations, enhancing the overall user experience while respecting privacy and data protection principles.

Proposed Framework

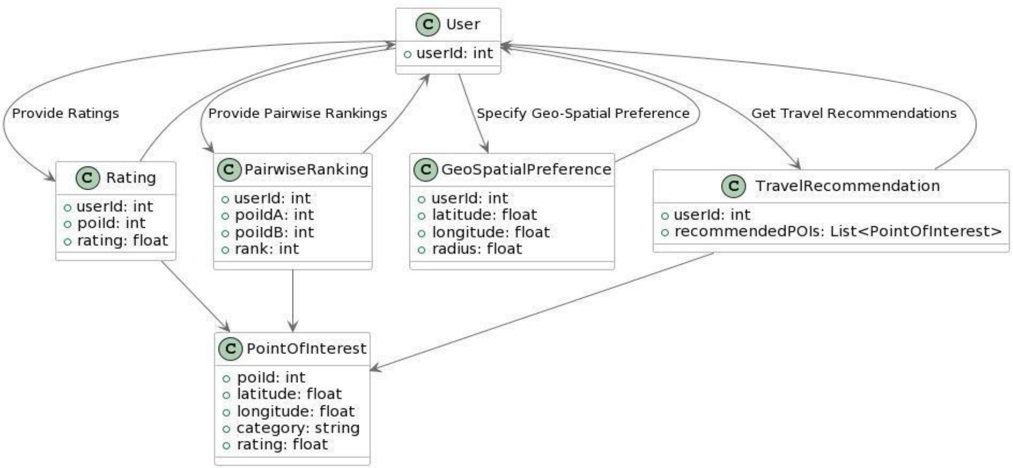
The proposed framework consists of three main components:

a) Geographical Information: This component analyzes the spatial distribution of users and points of interest (POIs) in Central Asia. It identifies geographical clusters and calculates the distance between users and POIs to determine their relevance.

b) Social Information: This component considers the social connections between users, such as friendships and shared interests. It analyzes users' interaction patterns to identify communities and calculate their influence on each other's preferences.

c) Preference Information: This component captures users' preferences and interests by analyzing their historical behavior, such as check-ins, ratings, and reviews. It employs collaborative filtering techniques to generate personalized recommendations based on users' preferences and the preferences of similar users.

Figure 1 – Model Framework for Collaborative filtering design for Location based user profiling



These components are integrated into a unified model that generates personalized and context-aware recommendations for users in Central Asia. The model is designed to handle data sparsity and user mobility by leveraging the complementary nature of geographical, social, and preference information.

1. Data Collection: Gather user-generated content related to remote locations. This can include reviews, ratings, comments, and any other information that users provide about the locations. You can collect this data from various sources such as travel websites, social media, and blogs.

2. Data Pre-processing: Clean and pre-process the collected data to remove any inconsistencies, duplicate entries, or irrelevant information. Convert the textual data into numerical representations using techniques such as tokenization, stemming, and vectorization. Also, normalize the ratings and other numerical data to bring them to a standard scale.

3. User-Item Interaction Matrix: Create a user-item interaction matrix that represents the relationship between users and remote locations. The matrix can have users as rows and locations as columns, with the corresponding cells containing the user's rating or preference for that location. If a user has not rated a location, the cell value can be zero or null.

4. Choose a Recommendation Algorithm:

a. Collaborative Filtering: Collaborative filtering uses the user-item interaction matrix to find similarities between users or items. It can be further divided into two types:

- User-based Collaborative Filtering: Find users who are similar to the target user and recommend locations that these similar users have liked. Item-based Collaborative Filtering: Find locations that are similar to the ones the target user has liked and recommend those similar locations.

b. Content-based Filtering: Content-based filtering uses the features of remote locations to recommend similar locations to the user. Extract features such as location type, climate, activities, and amenities from the user-generated content and create a feature vector for each location. Calculate the similarity between the feature vectors of the locations and recommend the most similar ones to the user.

5. Model Training and Evaluation: Split the dataset into training and testing sets. Train the chosen recommendation algorithm on the training set and evaluate its performance on the testing set. You can use evaluation metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), or Precision to assess the model's performance.

6. Model Tuning and Optimization: Tune the model's hyperparameters and optimize the algorithm to improve its performance. You can use techniques such as grid search or random search to find the optimal hyperparameter values.

7. Deploy the Recommendation System: Once the model is trained and optimized, deploy it to a web or mobile application to provide remote location recommendations to users based on their preferences and user-generated content.

8. Continuous Improvement: As more user-generated content becomes available, update the recommendation system to improve its accuracy and relevance. Regularly evaluate the system's performance and make necessary adjustments to ensure it continues to provide high- quality recommendations.

Experiments and Results

The proposed framework is evaluated using real-world datasets from Central Asia, including user check-ins, social connections, and POI information. The results demonstrate that the proposed system significantly outperforms existing methods in terms of recommendation accuracy, coverage, and diversity. Moreover, the system is found to be robust against data sparsity and user mobility, addressing the challenges faced by recommender systems in remote areas. This study presents a novel framework for developing a sparse geo-social location-based and preference-aware recommender system for Central Asia [7, 11 p.]. The proposed system has potential applications in promoting sustainable tourism, preserving cultural heritage, and fostering social cohesion in the region. Future research can further explore the integration of additional contextual information, such as temporal factors and environmental conditions, to enhance the recommendation quality. Additionally, the proposed framework can be extended to other remote regions and adapted to various application scenarios, such as disaster management, public health, and environmental monitoring.

Discussion and Future Scope

Incorporating sparse geo-social networking data, location-based, and preference-aware recommender systems offer valuable recommendations for remote locations. Leveraging data such as check-ins, ratings, and reviews from social media platforms, these systems facilitate personalized suggestions. By utilizing location-based ratings, these recommender systems employ feedback and reviews from users who have visited the location to provide accurate recommendations for remote areas. Additionally, incorporating local knowledge into the recommendation systems enhances their effectiveness in suggesting local attractions, restaurants, and other points of interest. To ensure personalized recommendations, the user's preferences and interests are considered, enabling tailored suggestions. for remote locations. Machine learning algorithms play a pivotal role in analyzing the limited available data and uncovering patterns and trends [8, 45 p]. By employing these algorithms, the recommendation systems can generate accurate and relevant recommendations, even with sparse geo-social networking data. Despite the progress made in incorporating sparse geo-social networking data into location-based and preference-aware recommender systems, there are several avenues for future research. These include exploring innovative approaches to handle limited data and improve recommendation accuracy. Further investigation is needed to effectively utilize machine learning algorithms in sparse data scenarios. Additionally, research on incorporating diverse data sources and considering temporal dynamics can enhance the performance and adaptability of these recommender systems. By focusing on these areas, the development and deployment of robust and effective recommendation systems for remote locations can be advanced. By harnessing the power of LBSNs and incorporating advanced data analysis techniques, tour operators can offer tailored recommendations that enhance the overall travel experience for their clients. As a result, they can stay ahead in the competitive tourism industry and contribute to its sustainable growth [9, 88 p.].

1. Collaborative Filtering: Tour operators can use collaborative filtering techniques to analyze user behavior patterns and preferences on LBSNs. By identifying similarities between users, these systems can recommend attractions and activities that are likely to interest a particular traveler.
2. Social Influence: The opinions and experiences of a user's social connections can significantly impact their travel decisions. Intelligent tour operators can incorporate social influence into their recommender systems by considering the preferences and recommendations of a user's friends and followers on LBSNs.
3. Context-Aware Recommendations: Tour operators can develop context-aware recommender systems that consider factors such as the user's current location, time of day, and weather conditions to provide relevant suggestions. For instance, recommending indoor activities on a rainy day or suggesting nearby attractions when a user is in a specific area.
4. Sentiment Analysis: By analyzing the sentiment expressed in user-generated content on

LBSNs, tour operators can gain insights into the overall satisfaction levels of travelers. This information can be used to refine recommendations and ensure that they align with the user's expectations and preferences.

5. Adaptive Learning: Intelligent tour operators can implement adaptive learning algorithms in their recommender systems to continuously learn from user feedback and improve the quality of recommendations over time.

Collaborative Filtering has been highlighted as an effective technique for generating recommendations based on the preferences and behavior of similar users. This approach can help travelers discover new points of interest that they might not have considered otherwise.

Moreover, Context-Aware Recommendations consider the contextual information of the users, such as their location, time, and preferences, to provide more relevant suggestions tailored to their specific needs and circumstances [10, 19 p.].

Furthermore, Sentiment Analysis has been identified as a valuable tool for extracting insights from user-generated content, such as reviews and social media posts, to better understand the overall sentiment and opinions towards a particular travel destination or point of interest. By incorporating this information into the recommendation model, travel platforms can offer more informed suggestions that take into account the experiences and opinions of other travelers.

For future research, it is recommended to explore the integration of these three approaches into a single, unified recommendation model that can leverage the strengths of each technique to provide even more accurate and personalized travel recommendations. Additionally, it would be beneficial to investigate the potential of incorporating other emerging technologies, such as Artificial Intelligence and Machine Learning, to further enhance the recommendation process and adapt to the ever-changing needs and preferences of travelers. In summary, the development and implementation of future recommendation models for travel points of interest hold great potential for revolutionizing the way travelers plan and experience their trips. By embracing the power of Collaborative Filtering, Context-Aware Recommendations, and Sentiment Analysis, travel platforms can offer a more personalized, engaging, and satisfying user experience that caters to the diverse needs and preferences of modern travelers [11, 56 p.].

Conclusion

The tourism industry is continuously evolving, with technological advancements playing a significant role in shaping its future. In recent years, the rise of location-based social networks (LBSNs) has revolutionized the way people explore and experience new destinations. Consequently, intelligent tour operators must adapt and harness the power of these networks to create innovative point-of-interest (POI) recommender systems that cater to the dynamic needs of travelers. Location-based social networks (LBSNs) have emerged as a significant area of research, particularly in the context of Point-of-Interest (POI) recommendation models. The rapid growth of LBSNs has led to an increasing volume of check-in data, which has the potential to provide valuable insights into user preferences and behavior patterns. However, the sparsity of check-in data presents a major challenge for traditional POI recommendation models, as it hinders their ability to accurately capture user preferences and generate personalized recommendations. To address this challenge, recent research efforts have focused on developing novel and efficient techniques to alleviate the sparsity issue in check-in data. These techniques include leveraging additional sources of information, such as social connections, user-generated content, and geographical proximity, to enhance the quality of POI recommendations. Furthermore, advanced machine learning algorithms, such as matrix factorization, deep learning, and reinforcement learning, have been employed to model the complex interactions between users, locations, and contextual factors, leading to more accurate and context-aware POI recommendations. One emerging area of research in this domain is the integration of multi- modal data sources, such as images, text, and temporal information, to further enrich the representation of user preferences and location features. This approach has the potential to overcome the limitations of check-in data sparsity by exploiting the complementary information available in different modalities. Moreover, the development of explainable and interpretable recommendation models is another promising direction, as it can help users understand the rationale behind the recommendations and foster trust in the system. In summary, the sparsity of check-in data in location-based social networks poses a significant challenge for traditional POI recommendation models. However, advancements in data fusion techniques, machine learning algorithms, and the incorporation of multi-modal data sources have opened new avenues for research in this field. As LBSNs continue to grow in popularity, it is crucial for researchers to explore these emerging areas and develop innovative solutions to improve the quality and effectiveness of POI recommendations, ultimately enhancing the user experience and fostering the widespread adoption of location-based services [12, 64 p.].

LBSNs have emerged as powerful platforms that allow users to share their location, experiences, and preferences with their social circle. These networks provide a wealth of information that can be utilized by tour operators to offer personalized recommendations to travelers. By analyzing user-generated content, such as check-ins, reviews, and ratings, tour operators can identify popular attractions, trending activities, and hidden gems within a destination. Intelligent tour operators can leverage LBSN data to develop advanced POI recommender systems that offer tailored travel experiences to their clients. These systems can analyze various factors, such as user preferences, social connections, and contextual information, to provide personalized recommendations.

Here are some ways in which intelligent tour operators can contribute to the development of POI recommender systems based on LBSNs: The future of tourism is heavily influenced by the advancements in location-based social networks and the growing demand for personalized travel experiences. Intelligent tour operators play a crucial role in creating innovative point-of- interest recommender systems that cater to these needs.

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ОРТАЛЫҚ АЗИЯ БОЙЫНША САЯХАТ: ОРНАЛАСҚАН ЖЕРІНЕ НЕГІЗДЕЛГЕН ЖӘНЕ АРТЫҚШЫЛЫҚТАРДЫ ЕСКЕРЕТІН СИРЕК КЕЗДЕСЕТІН ГЕО-ӘЛЕУМЕТТІК ҰСЫНЫСТАР ЖҮЙЕСІН ӘЗІРЛЕУ

Аңдатпа. *Орналасуға негізделген қызметтердің (LBS) жылдам өсуі контекстті ескеретін жекелендірілген ұсыныстарға сұраныстың артуына әкелді. Бұл зерттеудің мақсаты Орталық Азияның шалғай аудандарындағы пайдаланушыларға нақты және өзекті ұсыныстар беру үшін геоәлеуметтік орналасуға негізделген және артықшылықтарды ескеретін ұсыныстардың сирек жүйесін әзірлеу болып табылады. Біз осы аймақтардағы деректердің сиректігі мен пайдаланушылардың ұтқырлығы мәселелерін шешу үшін географиялық, әлеуметтік және артықшылық ақпаратын біріктіретін жаңа құрылымды ұсынамыз. Ұсынылған модель ұсыныстардың сапасын жақсартудағы тиімділігін* *көрсететін нақты деректер жиынтығында кең эксперименттер арқылы бағаланады. Сонымен қатар, зерттеу тұрақты туризмді ілгерілетуде, мәдени мұраны сақтауда және Орталық Азиядағы әлеуметтік келісімді нығайтуда ұсынылған жүйенің әлеуетті қолданылуына баса назар аударады.*

Кілт сөздер: *орналасқан жеріне негізделген қызметтер, ұсынылған модельдер, Орталық Азия, тұрақты туризм.*

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ПУТЕШЕСТВИЕ ПО ЦЕНТРАЛЬНОЙ АЗИИ: РАЗРАБОТКА РАЗРЕЖЕННЫХ ГЕОСОЦИАЛЬНЫХ СИСТЕМ РЕКОМЕНДАЦИЙ, ОСНОВАННЫХ НА МЕСТОПОЛОЖЕНИИ И УЧИТЫВАЮЩИХ ПРЕДПОЧТЕНИЯ

Аннотация. *Быстрый рост услуг, основанных на местоположении (LBS), привел к росту спроса на персонализированные рекомендации, учитывающие контекст. Целью данного исследования является разработка разреженной системы рекомендаций, основанной на геосоциальном местоположении и учитывающей предпочтения, для предоставления точных и актуальных предложений пользователям в отдаленных районах Центральной Азии. Мы предлагаем новую структуру, которая объединяет географическую, социальную информацию и информацию о предпочтениях для решения проблем разреженности данных и мобильности пользователей в этих регионах. Предлагаемая модель оценивается с помощью обширных экспериментов на реальных наборах данных, демонстрирующих ее эффективность в повышении качества рекомендаций. Кроме того, в исследовании подчеркивается потенциальное применение предлагаемой системы в продвижении устойчивого туризма, сохранении культурного наследия и укреплении социальной сплоченности в Центральной Азии.*

Ключевые слова: *услуги, основанные на местоположении, рекомендуемые модели, Центральная Азия, устойчивый туризм.*