Developing a smart travel recommendation system through AI-enhanced software engineering

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Abstract

Travel recommendations has always been an essential part of human life, going back to the earliest days of civilization when people traveled for a variety of reasons. Initially, recommendations were based on the collective experiences of the community. The development of modern recommender systems corresponded with as information technology advances, it is influencing every industry and service sector, including travel and tourism. Generic recommender engines were the first on the path, followed by personalized recommender systems and contextualized personalization with the development of artificial intelligence. The use of social media is also on the rise in the modern day, and big data from these platforms is becoming a crucial resource for many analytics, recommender systems included. This study's features, limits, and evolution of travel recommender systems are all covered in length in this publication. We also used the algorithms which are used in classification and recommendation systems, also metrics which can be used to assess how well the algorithms—and hence the recommenders—perform.

KEYWORDS: Recommender System, Artificial Intelligence, Destination Recommendation, Hybrid recommender system

1. Introduction and Background

In rapidly developing countries such as India, the travel and tourism industry has grown to be one of the largest service sectors in recent years. Now a days Artificial Intelligence can be very useful for recommendation. Artificial Intelligence (AI) has revolutionized recommendation systems by enabling them to analyze large amounts of data and provide personalized recommendations. AI-powered recommendation systems use machine learning algorithms to understand user preferences and behavior, thereby raising the recommendations' effectiveness and accuracy. This paper explores the role of AI in recommendation systems, including the algorithms used, challenges faced, and future directions in the field. By leveraging AI technologies, recommendation systems continue to evolve, recommending more appropriate and individualized material to clients.

A travel recommendation system is a technological tool designed to assist users in finding personalized travel suggestions based on their preferences, constraints, and historical behavior. These systems leverage different techniques from machine learning, data mining, and artificial intelligence to analyze large amounts of data, including user profiles, destination information, reviews, and ratings. Through collaborative filtering, content-based filtering, or hybrid approaches, these systems can generate tailored recommendations, such as destinations to visit, accommodations to stay in, activities to engage in, and even transportation options. By considering factors like user demographics, past travel experiences, interests, budget, and time constraints, these systems aim to provide relevant and accurate suggestions to improve the overall travel planning experience. Additionally, incorporating features like real-time updates, social interactions, and location-based services can further enrich the recommendation process, ensuring that users receive timely and contextually relevant suggestions. Travel recommendation systems plays an important role in simplifying travel decision-making, optimizing itinerary planning, and ultimately enhancing the overall travel experience for users.

Research in recommender systems faces several key challenges and areas for improvement. One significant issue is the lack of high-quality and exclusive recommender systems capable of providing personalized recommendations across diverse domains. This limitation restricts the ability of recommender systems to offer tailored suggestions, impacting user satisfaction and engagement. Additionally, the limited availability and quality of datasets for evaluating recommender system performance pose a significant challenge. Without access to comprehensive and high-quality datasets, IT could be difficult for researcher to evaluate their recommender's systems' efficacy and efficiency with accuracy [1]. Furthermore, recommender systems face potential issues connected to the cold-start problem, where they struggle to provide accurate recommendations for new users or items with limited data. Addressing this problem is essential for improving the accuracy and relevance of recommendations in various applications. [1]. a critical research gap in recommender systems concerning the collection of ratings from users. Specifically, it highlights the challenge of determining user satisfaction and the degree of satisfaction with a product when users do not provide explicit ratings. This gap creates important questions about how to effectively and accurately gather ratings. [2]. The existing literature lacks sufficient discussion on the challenges and limitations associated with the use of different big data technologies, artificial intelligence (AI), and operational research in the subject of tourism recommendation systems. While these technologies have gurantees for enhancing the personalization and effectiveness of recommendation systems in the tourism industry, their implementation is not without challenges. [3]

2. Research Work

2.1 Artificial Intelligence

The simulation of human intelligence processes by machines, particularly computer systems, is known as artificial intelligence. By using AI we can create digital computer or computer controlled robot which can perform tasks which are generally done by human. Machines can now learn from experience, adapt to new inputs, and carry out activities that humans would normally be unable to complete thanks to artificial intelligence (AI).Most AI examples that you hear about today are the chess-playing computers to self-driving cars, which are dependent on deep learning and natural language processing. Using these technologies, computers are to be trained to complete specific tasks by processing on large amounts of data and recognizing useful patterns from the data.

In the 1950s, symbolic approaches and problem solving became the primary goals of early AI research. The US Department of Defense was interested in this kind of work in the 1960s and started teaching computers to simulate fundamental human reasoning. In the 1970s, for instance, the Defense Advanced Research programs Agency (DARPA) completed street mapping applications. In 2003, DARPA created intelligent personal assistants, far before Siri, Alexa, or Cortana were popular.

The automation and formal reasoning that we see in computers today, such as efficient search and decision support systems that may be designed to supplement and even improve human abilities, were made feasible by this early work.

The capacity of AI to learn from data is one of its fundamental features. Different machine learning algorithms enable AI systems to evaluate vast data, identify patterns, and make judgements or forecasts without explicit programming. This has promoted the creation of AI applications like recommendation systems, virtual assistants, and autonomous vehicles.

Ethical considerations are crucial in AI development, particularly regarding privacy, bias, and accountability. As AI systems become more autonomous and integrated into society, ensuring they are designed and used responsibly is paramount. Researchers and policymakers are working to establish guidelines and regulations to address these ethical concerns.

2.2 Recommender System

They are become helpful resources for searching out and recommending to user's appropriate material [2]. They are mostly used when users require specific recommendations based on their preferences and likes when there are many possibilities or items to select from [1]. Recommender systems can evaluate user input and generate recommendations using wide assortment of machine learning algorithms and AI methods [2]. These methods can consist of content-based filtering, collaborative filtering, and hybrid approaches that blend several methods [4-6]. Recommender systems are used by a number of well-known websites and services, including Spotify, YouTube, Netflix, Google, Flipkart, Amazon, and Gaana.com, to offer consumers recommendations for songs, films, purchases, and other material. These systems can provide customized recommendations based on user data, helping clients find new content and selecting items with greater knowledge. Recommender systems are generally categorized as three different types' viz. content-based recommender systems, collaborative-filtering recommender systems and hybrid recommender systems [1,4].

2.2.1 Content-based Recommender System:

Recommender system based on content the information retrieval technique known as content-based filtering is based on semantic search. [7]. The cognitive filtering method is another name for content-based filtering. This method makes product references based on the customer's profile and the item profile of the client. When a user first launches the system, their profile is created. [8]. After examining the properties of the products and the users, it analyses the user interest and recommends the items. [9]. The items that are being advised are exactly like the things that the client has previously loved and they also fit the user's characteristics. Only when the attributes are presented in an appropriate and unambiguous manner does this strategy function effectively [10]. The user's profile and the item description are most useful in the content-based filtering strategy [6]. The steps for this method are as follows:

- It is compulsory to define the item attributes for recommendations.
- The qualities of the goods are compared to the preferences ofthe current user.
- Items are suggested based on the user's interests.

The primary function of CBF is to predict whether the active user will like or dislike the recommended item once the properties of the item and the user's profile are known [10].

2.2.2 Collaborative filtering-based Recommender System:

Product recommendations are made by collaborative filtering based on user and item similarity [6, 8]. Recommendations from the CF recommendation system depend on previous evaluations of products made by individuals who match the target user [8]. The main objective of collaborative filtering is to collect information about the behavior and opinions of previous users so that it may be compared to the current user's and whether or not they are similar [9]. The recommender system is able to create connection between people who have similar features and between things of interest to users who share their appearance because it tracks each user's rating, viewing, and purchasing histories [11]. Collaborative filtering offers reliable recommendation ideas and is easy to apply when working with small amount of data dependencies [12]. Additionally, collaborative filtering is categorized into three main categories, model based, memory based and hybrid based collaborative filtering.

2.2.3 Hybrid Recommender System:

A hybrid approach is one that combines two or more methods. One of the most recent developments in the different recommender system is this. A combination of these different systems is employed by the Hybrid [8]. It appears that Facebook's recommendation algorithm employs each of these strategies. The hybrid recommendation makes use of all available strategies, but it should be used with extreme caution as it may require a lot of work and produce inconsistent results. [13,14,15]

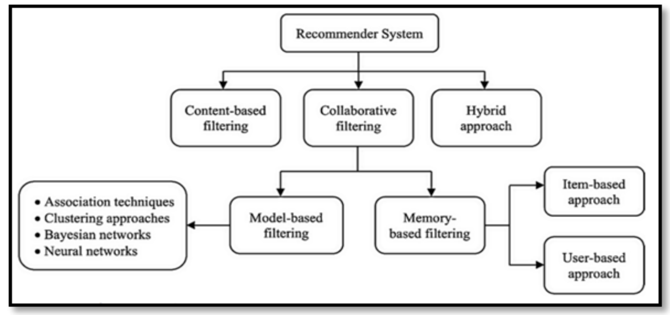


Fig-1: Types of RS [1]

3. Research Issues

Limited availability and quality of datasets for evaluating recommender system performance. The need for further research on optimizing the novelty, diversity, and accuracy of recommendations in hybrid recommender systems. Exploration of new techniques and approaches to raise the effectiveness and performance of recommender systems, such as using evolutionary algorithms or neural networks. [1]

The papers do not effectively concentrate the implications of the research for both theory and practice. A more thorough discussion of the practical applications and theoretical contributions of the study would strengthen the paper's impact and relevance. The paper could benefit from the inclusion of more visual aids, such as figures, tables, and diagrams, to illustrate the key points and improve the overall presentation. [1]

It not includes discuss the scalability of the future approach, which is essential for a large-scale tourism destination recommendation system. The scalability of the recommender system would depend on various factors like the number of users, destinations, and reviews.

It not discusses the real-world implementation of the future approach. It would be beneficial to provide a case study or real-world implementation to demonstrate the efficiency of the recommended approach in a practical setting [3].

4. K-Means ALGORITHM

An algorithm for unsupervised learning is K-Means clustering. Unlike supervised learning, this clustering does not utilize labeled data. K-Means splits the objects into clusters based on similarities and differences between the objects in each cluster.

K is an acronym for a number. The number of clusters that must be created must be specified to the system. K = 2, for instance, designates two clusters. The optimal or best value of K for a particular set of data can be determined in a certain method.

Working of K-Means clustering

Following flowchart will show how K-means clustering algorithm works:

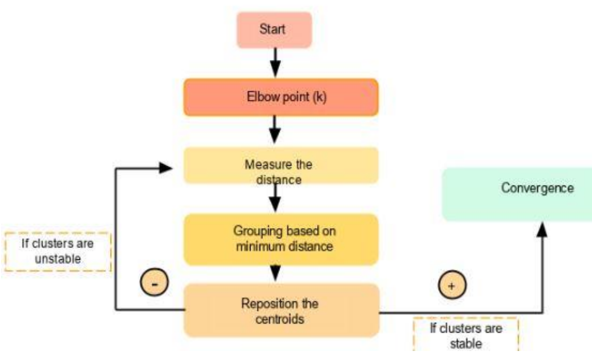


Fig-2: Flow of K-Means clustering algorithm

Finding clusters in the raw data that is provided is the aim of the K-Means algorithm. There are two methods by which we can perform it. If we provide the value of K (e.g., 3, 4, 5), we may apply the trial and error procedure. We continue adjusting the value as we go along until we obtain the optimal clusters.

Another way to find the value of K is to apply the Elbow technique. After determining the value of K, the system will randomly assign a particular amount of centroids and calculate the distance among each data point and these centroids. As a result, it assigns those points to the corresponding centroid that is the closest to the starting point. The centroid which is closest to each data point will be allocated to it. As a result, we have K initial clusters.

For the new created clusters, it will find new centroid. The position of the centroid moves depended to the randomly allocated previous one.

Once more, this new centroid point is used to calculate the distance between each point. If required, the data points are moved to the new centroids, and a fresh calculation is made of either the mean position or the new centroid.

The iteration continues to indicate no convergence if the centroid moves. However, the centroid will reflect the outcome after it stops advancing, indicating that the clustering process has completed.

Let's take a visualization example to understand this example.

We need to determine the number of clusters that this data collection from a grocery store has to be distributed over. We divide it into the following steps to get the ideal number of clusters:

Step 1:

To find the number of clusters, the Elbow approach is the most effective method. Using the elbow approach, K-Means clustering is applied to the dataset.

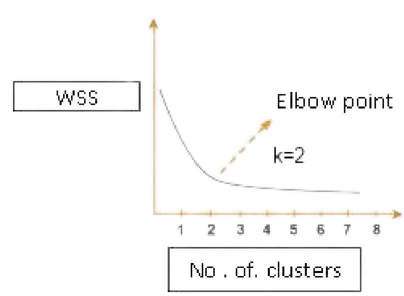
Next, we determine the ideal number of clusters that can be generated for a particular data set using within-sum-of-squares as a measure. The total of the squared distances between each cluster member and its centroid is known as the within-sum-squares (WSS).

$$WSS = \sum_{i=1}^{m} (x_i - c_i)^2$$

Where x_i = data point and c_i = closest point to centroid

With every K value, the WSS is calculated. The ideal value is determined by taking the value of K, which has the least amount of WSS.

Now, we create a curve between WSS and the number of clusters.



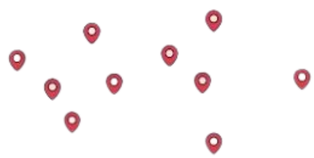
Here, WSS is on the y-axis and number of clusters on the x-axis.

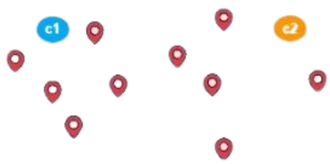
As the K value rises from 2, you can observe that the value of WSS changes quite gradually.

Therefore, the elbow point value can be used to determine the ideal value of K. Either two, three, or at most four should be the number. Beyond that, though, the value in WSS stabilizes as the number of clusters increases without significantly altering it.

Step 2:

Let's consider that these are our delivery points:





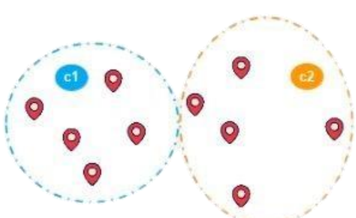
We can randomly initialize two points called the cluster centroids.

Here, C1 and C2 are the centroids assigned randomly.

Step 3:

Each data point is now assigned to the centroid that is closest to it after the distance between each location and the centroid is measured.

This is how the initial grouping is done:

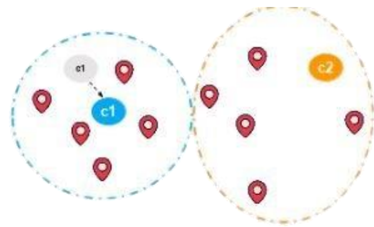


Step 4:

Find the first group's true centroid of data points.

Step 5:

Change the arbitrary centroid to the true centroid.



Step 6:

Find the second group's true centroid of data points.

Step 7:

Change the arbitrary centroid to the true centroid.

Step 8:

It is said that the k-means algorithm has converged when the cluster becomes static.

The following illustrates the final cluster, which has centroids c1 and c2:

5. Proposed System

The proposed architecture's conceptual framework comprises three main sub-processes: user profiling, content filtering, and trip planning. These processes integrate various areas of computer science research, such as artificial intelligence and operational research. In artificial intelligence, user profiling is treated as a learning problem that leverages users' past interactions. The system learns the user's profile rather than relying on explicit user input, typically utilizing Machine Learning techniques. The filtering process aims to categorize new information based on previously labeled data as interesting or uninteresting, generating a predictive model to assess a user's interest level in new items.

In operational research, the procedure of discovery of the nearest place leads to a combinatorial optimization problem, akin to the traveling salesman problem. Metaheuristics are employed to find near-optimal solutions within a reasonable timeframe.

The architecture consists of three main processes: user profiling, content filtering, and trip planning.

User Profiling: User data collection is crucial, involving scenarios allows the extraction of user preference. Users explicitly indicate their interests, such as selecting a city to find nearby places. No login is required. Users then specify criteria like historical sites, hotel availability, restaurants, and cuisine preferences. Demographic data can be used to make recommendations for new users, addressing the cold start problem. [18,19]

Content Filtering: Recommendation techniques rely on the results of the profiling process. The process considers all modules and uses a hybrid model for recommendations, returning a list of items based on user preferences.

Trip Planning: Based on the recommended list, users can arrange their travel with ease, selecting the best location for their preferences.

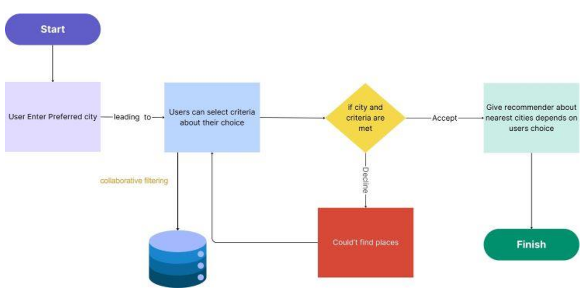


Fig -3: Flow of Proposed System

6. Result

In terms of user profiling, the system successfully collected and extracted user preferences from various scenarios, allowing users to indicate their interests without the need for a login. Criteria such as historical landmarks, hotel accommodations, and restaurant preferences were effectively captured, with demographic data proving useful in generating recommendations for new users, addressing the cold start problem.

The content filtering process relied on the results of the profiling process to deliver recommendations. A hybrid model was employed, resulting in a curated list of items tailored to user preferences. Users were empowered by the recommended list, enabling them to seamlessly plan their trips based on their preferences. The system demonstrated efficiency in suggesting suitable destinations, enhancing the overall trip planning experience.

The integration of user profiling, content filtering, and trip planning processes proved effective in providing personalized recommendations. Initial feedback from users indicated a high level of satisfaction with the system's ability to recommend relevant and interesting destinations. The suggested architecture is promising for further development and enhancement, particularly in refining recommendation algorithms and expanding the range of user preferences considered.

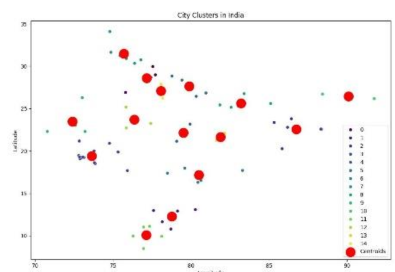


Fig -4: Result by K-Means clustering

7. Conclusion

In this study, we proposed an architecture for user profiling, content filtering, and trip planning that integrates various areas of computer science research, including artificial intelligence and operational research. Our results demonstrate the suggested architecture's usefulness in supplying specific guidance for trip planning. The user profiling process successfully collected and extracted user preferences, while the content filtering process efficiently categorized new information based on user interests. The trip planning process empowered users to plan their trips based on curated recommendations, enhancing their overall travel experience.

Moving forward, there is potential to further refine the recommendation algorithms and expand the range of user preferences considered. Additionally, future research could explore the scalability of the architecture to accommodate a larger user base and a broader range of destinations. Overall, the proposed architecture shows promise in enhancing the user experience in trip planning and could have applications in other recommendation systems as well.

Once the sets of elements considered relevant to the tourist are selected, our system will plan an appropriate trip by combining these items using operational research techniques. This architecture will be implemented using advanced technologies, such as AI tools, machine learning techniques, and the Internet of Things.

8. References

1) Deepjyoti Roy and Mala Dutta, "A systematic review and research perspective on recommender systems", Journal of Big Data, Springer Open, 2022

2) Nitin Mishra, Saumya Chaturvedi, Aanchal Vij, Sunita Tripathi, "Research Problems in Recommender systems", Journal of Physics:Conference Series, 2021

3) Khalid AL Fararni, Fouad Nafis, Badraddine Aghoutane, Ali Yahyaouy, Jamal Riffi and Abdelouahed Sabri, "Hybrid Recommender System for Tourism Based on Big Data and AI: A Conceptual Framework", BIG DATA MINING AND ANALYTICS, Volume 4, Number 1, March 2021

4) Deepak Kumar Jain, Akshi Kumar, Vibhuti Sharma, "Tweet recommender model using adaptive neuro-fuzzy inference system", Future Generation Computer Systems on Science Direct, 112, pp. 996- 1009, 2020

5) Harleen kaur, Gourav Bathla," Techniques of Recommender System", International Journal of Innovative Technology and Exploring Engineering, 8, pp. 373-379, 2019

6) Seema P. Nehete, Satish R. Devane, "Recommendation Systems: past, present and future", International Conference on Contemporary Computing (IC3), 2018

7) Nehete, S.P. and Devane, S.R., "Recommendation Systems: past, present and future". Eleventh International Conference on Contemporary Computing (IC3) pp. 1-7 IEEE, August 2018.

8) Patel, A., Thakkar, A., Bhatt, N. and Prajapati, P.,"Survey and Evolution Study Focusing Comparative Analysis and Future Research Direction in the Field of Recommendation System Specific to Collaborative Filtering Approach". In Information and Communication Technology for Intelligent Systems Springer, Singapore pp. 155-163., 2019

9) Yanxiang, L., Deke, G., Fei, C. and Honghui, C. "User-based clustering with top-n recommendation on cold-start problem". Third International Conference on Intelligent System Design and Engineering Applications IEEE pp. 1585-1589, January 2013.

10) Mustafa, N., Ibrahim, A.O., Ahmed, A. and Abdullah, A., "Collaborative filtering: Techniques and applications." International Conference on Communication, Control, Computing and Electronics Engineering (ICCCCEE) , IEEE , pp. 1-6, January 2017.

11) Ghodsad, P.R. and Chatur, P.N "Handling User Cold-Start Problem for Group Recommender System Using Social Behaviour Wise Group Detection Method". International Conference on Research in Intelligent and Computing in Engineering (RICE), IEEE pp. 1-5, August 2018.

12) Li, J., Zhang, K., Yang, X., Wei, P., Wang, J., Mitra, K. and Ranjan, R.,"Category Preferred Canopy–K-means based Collaborative Filtering algorithm". Future Generation Computer Systems, 93, pp.1046-1054, 2019.
    A. Gunawardana and C. Meek, "A unified approach to building hybrid recommender systems," in Proceedings of the Third ACM Conference on Recommender Systems, RecSys '09, (New York, NY, USA), pp. 117–124, ACM, 2009.

13) S.-T. Park, D. Pennock, O. Madani, N. Good, and D. DeCoste, "Na¨ıve filterbots for robust cold-start recommendations," in Proceedings of the 12th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '06, (New York, NY, USA), pp. 699–705, ACM, 2006.

14) S.-T. Park and W. Chu, "Pairwise preference regression for cold-start recommendation," in Proceedings of the Third ACM Conference on Recommender Systems, RecSys '09, (New York, NY, USA), pp. 21–28, ACM, 2009.

15) Designing Recommender Systems for Tourism, Tobias Berka∗and Manuela Pl¨oßnig, December 3, 2011

16) M. Vozalis and K. G. Margaritis, On the enhancement of collaborative filtering by demographic data, Web Intelligence and Agent Systems, vol. 4, no. 2, pp. 117–138,2006.

17) A. T. Nguyen, N. Denos, and C. Berrut, Exploitation des donnees ”disponibles ´ a froid” pour am ` eliorer le d ´ emarrage ´a froid dans les syst ` emes de filtrage d’information, in ` Actesdu XXIV Congres d’INFORSID `, Hammamet, Tunisie, 2006,pp. 81–95.

18) K. H. Lim, J. Chan, C. Leckie, and S. Karunasekera,Personalized tour recommendation based on user interests and points of interest visit durations, in Proc. 24th Int. Joint Conf. Artificial Intelligence, Buenos Aires, Argentina, 2015,pp. 1778–1784.

19) I. R. Brilhante, J. A. Macedo, F. M. Nardini, R. Perego, and C. Renso, On planning sightseeing tours with TripBuilder, Information Processing & Management, vol. 51, no. 2, pp.1–15, 2015.