University of Jeddah
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Restaurant Recommendation System Based on User Ratings with Collaborative Filtering

Phase3

Final Report

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Abstract:

Choosing restaurants can be a cumbersome task for every person, highlighting the necessity of utilizing computational methods to provide recommendations for users. The paper deals with the design and development of an advanced recommendation system using an approach for restaurant feature improvement that is personalized to the customer for changing behavior and preferences. The proposed system uses a collaborative filtering-based approach, which focuses on user reviews collected from reliable sources like Kaggle to recommend restaurants. It ranges from data collection, which consists of information on restaurants and users' ratings, to cleaning the data to ensure quality data is guaranteed. Using the collaborative filtering algorithm, it analyzes users with similar interests based on their rating patterns. The system uses the Pearson correlation function to compute rating similarities and hence determines and prioritizes users with similar interests. Based on this, the system makes personalized recommendations for restaurants by averaging the highest ratings from similar users, weighted by their Pearson correlation scores. In the evaluations done with Root Mean Square Error, the system tends to have high predictive accuracy, which further enhances its capability of acting as an effective tool in making informed dining choices.

Introduction:

Humans are faced with situations on a daily basis that require them to make a decision or choose something. The multiplicity of options available makes people confused in making a decision or choice. This problem can be overcome by providing suggestions or recommendations from other people. Nowadays, methods for solving this problem have evolved and have become dependent on implementing a recommendation system to suggest options based on a specific criterion (user reviews, for example). Recommendation systems are often used in e-commerce, marketing, or online applications. The recommendation approach is implemented with the aim of knowing potential users or customers. On the other hand, it is implemented to provide recommendations about a product or facility related to the interests of users. Providing recommendations can have an impact on the product or facility. The impact may be positive if users find it suitable for them and fits their needs [1] [2].

The collaborative filtering algorithm operates under three key assumptions: individuals have similar preferences and interests, these preferences remain consistent over time, and we can infer a person's choices by looking at their previous preferences. Based on these assumptions, the collaborative filtering method links the behavior of one user with that of others to identify their closest peers, using the interests or preferences of these peers to predict the user's own inclinations. A well-known example of this approach is Amazon, which utilizes collaborative filtering to suggest products to its customers [3]. Collaborative filtering relies on various factors to generate recommendations, including users' past behaviors, items they have bought, and the ratings given to those purchased items [4]. The paper presents the design and development of an advanced recommendation system intended for continuous improvements to restaurant features in accordance with the personalized behaviors and preferences of customers. Specific steps in the research process will include dataset preparation, filtering, collaborative filtering, Pearson correlation analysis, recommendations, and evaluation.

Background/Related Work:

The study [5] aims to create a system that recommends movies using three algorithms: content-based filtering, collaborative filtering, and the Pearson correlation coefficient. This system is a web-based platform that suggests movie titles based on various factors, including online searches, item descriptions, user borrowing habits, historical movie data, and individual user preferences. The implementation proves successful, and the combination of these algorithms can be applied beyond just movie recommendations; it is also suitable for other platforms such as e-learning, eCommerce, social media, news article sites, product selection, and more.

In paper [6], a recommendation system for ideological and political education is proposed, utilizing the analytic hierarchy process (AHP) alongside an enhanced collaborative filtering algorithm. Initially, the recommendation model accounts for the temporal aspect of student ratings by transforming it into a Markov decision process. Subsequently, the collaborative filtering algorithm is integrated with reinforcement learning techniques to create an optimization model for student ratings based on timestamp data. To quantify students' course preferences, AHP is employed to convert behavioral data into preference values. To address data scarcity issues, missing values are estimated using prediction score rounding and optimization boundary completion methods. Experimental results demonstrate the feasibility of the proposed system, highlighting its strong accuracy and convergence performance. This ideological and political education recommendation system offers significant insights for advancing ideological and political education in the context of big data.

The objective of paper [4] is to enhance the accuracy and performance of a standard filtering technique. While various methods can be employed to create a recommendation system, content-based filtering is the most straightforward approach. It takes user input, reviews their history and past behavior, and suggests a list of similar movies. In this study, K-NN algorithms and collaborative filtering are utilized to primarily improve the accuracy of results in comparison to content-based filtering. This method leverages cosine similarity in conjunction with the k-nearest neighbor approach and a collaborative filtering technique, addressing the limitations associated with content-based filtering. Although Euclidean distance is often preferred, cosine similarity is chosen here because the accuracy of the cosine angle and the relative distances between movies remain nearly constant.

In General, A recommendation system makes suggestions for particular items to the users and can be provided for applications like social media, e-learning, web news, and e-commerce. Collaborative filtering is another important algorithm that provides recommendations in a personalized way, especially in the case of large datasets. It works by finding similarities among the users, assuming that similar users will give the same rating to the same item. Segmentation of users is the approach of this method [7]. Once similarities between items are computed, collaborative filtering can predict the missing values. There are different ways to compute similarity, such as Pearson Correlation and Spearman Rank; however, studies have proved that Weighted Pearson Correlation demonstrates good predictive power. The selection method may depend on different variations in data, and the completeness of data is important to make proper recommendations. This data sparsity issue makes proposing new collaborative filtering techniques that incorporate clustering algorithms necessary. Several previous studies have proposed enhancements to similarity calculation in order to improve the recommendation accuracy, although Pearson Correlation may produce inaccurate results sometimes in certain contexts [8] [9].

Approach:

Figure 1 shows the research methodology steps. It comprises six stages. These stages are dataset preparation, dataset filtering, collaborative filtering, Pearson correlation, recommendation, and evaluation.

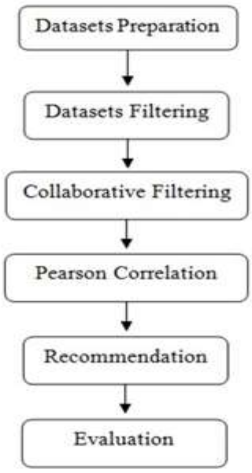

Figure 1: Methodology Steps

Experiments:

First the dataset was selected. Restaurant and Consumer Recommendation System Dataset [10] was used. Then important columns was selected to be used in recommended system.

	placeID	name	address
0	134999	Kiku Cuernavaca	Revolucion
1	132825	puesto de tacos	esquina santos degollado y leon guzman
2	135106	El Rincón de San Francisco	Universidad 169
3	132667	little pizza Emilio Portes Gil	calle emilio portes gil
4	132613	carnitas_mata	lic. Emilio portes gil

Figure 2: important columns

Collaborative filtering

For each user get rating for all restaurants, if there is no rating by a user to a restaurant fill 0.

placeID	132560	132561	132564	132572	132583	132584	132594	132608	132609	132613	...	135080	135081	135082	135085	135086	135088	135104	135106	135108	135109
userID																					
U1001	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
U1002	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0
U1003	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
U1004	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	0.0	0.0
U1005	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Figure 3: Collaborative filtering

Final recommendation results

	placeID	name
0	132733	Little Cesarz
1	132613	carnitas_mata
2	135104	vips
3	132733	Little Cesarz
4	132613	carnitas_mata
5	132630	palomo tec
6	132584	Gorditas Dona Tota
7	132663	tacos abi
8	135104	vips
9	132630	palomo tec

Figure 4: Final recommendation results

Discussion and Conclusion

From the data preprocessing to collaborative filtering and nearest neighbors, a few key takeaways were obtained for the recommendation system. Among those, important ones were related to the proper cleaning of the data, feature selection, and making proper recommendations through collaborative filtering on sparse data. Future ideas to further improve the recommendation system include exploring more advanced algorithms such as matrix factorization and deep learning models, implementing updates in real-time for faster adaptation to user preferences, incorporating content-based filtering for a hybrid approach, and adding metrics that will be used for quantitative evaluation of system performance. This will be achieved by the incorporation of user feedback, diversity in recommendations, optimizing scalability and performance, enhancement of personalization due to contextual features, A/B testing for comparing algorithms, and enhancement in interpretability by explanations. The various ways through which recommendation systems can evolve to recommendations that are accurate, personalized, and engaging include the following: improving user satisfaction and system performance by manifold.

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Team Contribution:

Task	Member(s)
Phase 1	All members
Phase 2	All members
Phase 3	All members
Phase 4	All members