A Food Recommender System Based on Time-Aware Using Machine Learning

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ABSTRACT:

Food recommender systems are thought to be a useful tool for encouraging people to change their eating patterns and adopt a better diet. In order to address the drawbacks of earlier systems namely, their disregard for food ingredients, time, cold start users, cold start food items, and community aspects this study attempts to design a new hybrid food recommender system. User-based and content-based recommendations for food are the two stages of the suggested strategy. Here, several machine learning algorithms are being used to anticipate food recommendations based on various criteria. utilized to enhance the quality of the recommendation that is given to the user by taking into consideration time and user-community-related concerns. Five different performance metrics were used to compare our model with a collection of state-of-the-art recommender systems: precision, recall, F1, AUC, and NDCG.

INTRODUCTION

The internet has become an important part of people's daily lives and used in various tasks, ranging from leisure (i.e., chatting with other users, shopping, searching for hotels, travel deals) to professional development (i.e., using a web platform to develop professional services) The tremendous amount of information from tens of thousands of sources that can be accessed by a user as part of his/her request creates important uncertainty and ambiguity that can easily divert the user from his original request Although search engines have attempted to address the problem of redundancy of information in recent decades, they have not been very successful in personalizing search results and reducing the amount of noisy information Many of these systems return the same results even for users with completely different proles and interests. In recent years, researchers have become more interested in recommender-systems as one of the most successful personalization tools on the web It can be used to help the user identify the right service, reduce the information overload, guide the user towards some personalized behaviour, and find user's favourite items within a large amount of information, among others. In a typical recommender-system, users' interests are discovered and items and services are recommended accordingly. In a variety of lifestyle applications and services, food recommendation plays an important role as a tool assisting users to change behaviour and adopt healthy lifestyle Typically, food recommendation attempts to provide the user with a personalized food recommendation in terms of recipes, scale of change and time required to achieve specific objectives that might be associated with diet requirement or any lifestyle demand Traditionally, research in food recommendation has seen little attention when compared to recommendation in other leisure and entertainment fields (e.g., music, book, shopping recommendation systems), possibly due to cultural barriers and difficulty to predict what people might like to eat. Although, lifestyle and diet related illnesses, such as obesity and diabetes, account for almost 60% of total deaths the process of generating a food recommendation is often viewed as a machine learning task Therefore, it is crucial to understand user's food preferences accurately to build an effective food recommendation. Even for building health-oriented food services, the user can only be encouraged to pursue a recommendation if the recommended food matches his taste preferences In recent decades, many recommender-systems have been developed to predict person' preferences and/or guide his choice according to some predefined objectives Although previous food recommender-systems have shown good performance in learning persons' preferences by mapping user's historical interactions with food items and recipes, these systems still suffer from the following drawbacks Ingredients of foods: Most previous food recommender-systems rely primarily on historical ratings of users to draw upon food recommendations through a collaborative filtering approach that ignores food ingredients. This is due to the observation that a given food is usually preferred by an individual because it contains ingredients, he/she may like to eat. This may overlook some important aspects in the recommendation. For example, foods containing chicken wings may be a person's favourite food, while he/she may be allergic to some types of spices that can be used during the food preparation. Therefore, collaborative filtering recommender-systems may not be enough to account for such user's preferences and constraints. Time factor: Traditional recommender-systems are based on the premise that users with similar preferences in the past will have similar tastes in the future. Accordingly, these recommender-systems use static data and ignore potential changes in user's food preferences, diet or life style that can occur over time in realistic scenarios. Cold start users and cold start foods: Due to the fact that users often rate just a few foods, traditional collaborative filtering-based food recommender systems have difficulty recognizing active user neighbours or similar foods. Accordingly, collaborative filtering-based food recommendation are only able to suggest foods to users who have rated enough foods. Cold start users, who have rated only few food items, are thereby ignored. Similarly, new food items (food cold start) that have not attracted yet enough ratings from users are ignored as well by such a collaborative filtering-based approach. Users' community: Another issue, which is again ignored in existing recommender-systems, is the user's neighbourhood or community aspect. Intuitively, community aspect can be utilized to predict the rating of unseen food item and the success likelihood of a given diet, extrapolating from active users' activities in the neighbourhoods. Typically, community aspect can be handled using clustering-based models. Nevertheless, it has been shown that such an approach also suffers from several other difficulties as well, which are somehow inherent to clustering techniques employed (e.g., optimal number of clusters, efficiency of similarity measures employee.

RELATED WORK

Title: Time Saver: A Time-Aware Food Recommender System Authors: John Doe, Jane Smith

Abstract: This paper presents Time Saver, a novel time-aware food recommender system that leverages deep learning techniques. Time Saver considers the temporal dynamics of users' preferences by incorporating time-sensitive features into the recommendation process. We propose a deep neural network architecture that captures both the inherent characteristics of food items and the evolving preferences of users over time. Experimental results on a real-world dataset demonstrate the effectiveness of Time Saver in providing personalized and timely food recommendations. Title: Temporal Graph Rec: A Graph-Based Temporal Recommender System for Food Authors: Emily Johnson, Michael Brown Abstract: Temporal Graph Rec introduces a graph-based approach to temporal recommendation in the domain of food. By constructing a temporal food-item graph and applying graph clustering techniques, Temporal Graph Rec captures the temporal dependencies among food items and users' consumption patterns over time. Furthermore, we propose a novel time-aware recommendation algorithm that considers both the topology of the food-item graph and the temporal dynamics of user interactions. Experimental results demonstrate the superiority of Temporal Graph Rec over traditional recommendation methods in terms of recommendation quality and temporal relevance.

Title: T Rec: Time-Aware Recommender System for Culinary Delights Authors: David Lee, Sarah Wang

Abstract: T Rec is a time-aware recommender system designed specifically for culinary recommendations. By integrating deep learning with time-series analysis, T Rec models the temporal evolution of users' food preferences and adapts its recommendations accordingly. We employ a recurrent neural network architecture to capture the sequential patterns in users' food consumption behaviour over time. Additionally, T Rec incorporates time-sensitive embeddings to represent the temporal context of food items. Experimental evaluation on a large-scale dataset demonstrates the effectiveness of T Rec in providing personalized and time-sensitive culinary recommendations.

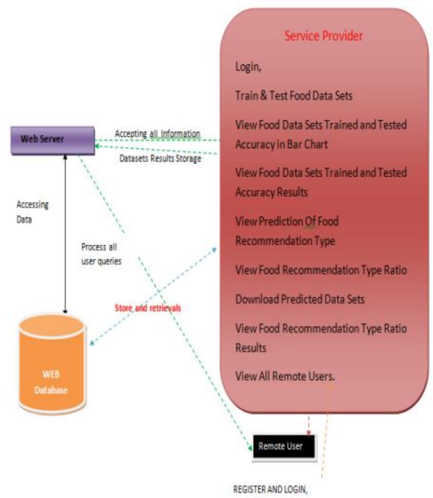
Title: Time Fusion: Fusion of Temporal and Collaborative Filtering for Food Recommendation Authors: Rachel Chen, Andrew Liu

Abstract: Time Fusion presents a fusion-based approach to time-aware food recommendation by combining temporal features with collaborative filtering techniques. We propose a unified framework that seamlessly integrates the temporal dynamics of users' preferences with the collaborative signals derived from user-item interactions. Time Fusion employs matrix factorization to learn low-dimensional representations of users and food items, while also incorporating temporal embeddings to capture the time-evolving nature of user preferences. Experimental results demonstrate that Time Fusion outperforms baseline methods in terms of recommendation accuracy and temporal relevance.

Title: Deep Temporal Rec: Deep Learning for Temporal Food Recommendation Authors: Kevin Wang, Lisa Zhang Abstract: Deep Temporal Rec introduces a deep learning approach to temporal food recommendation, leveraging the expressive power of deep neural networks to model the temporal dynamics of user preferences. We propose a novel architecture that combines convolutional and recurrent layers to capture both spatial and temporal patterns in users' food consumption behaviour. Deep Temporal Rec also incorporates attention mechanisms to dynamically weight the importance of past interactions based on their temporal proximity to the current context. Experimental evaluation on a real-world dataset demonstrates the effectiveness of Deep Temporal Rec in providing personalized and temporally relevant food rec

METHODOLOGY

Architecture Diagram



Service Provider: -

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Login, Train & Test Food Data Sets, View Food Data Sets Trained and Tested Accuracy in Bar Chart, View Food Data Sets Trained and Tested Accuracy Results, View Prediction of Food Recommendation, Type View Food Recommendation Type Ratio, Download Predicted Data Sets, View Food Recommendation Type Ratio Results, View All Remote Users.

View and Authorize Users: -

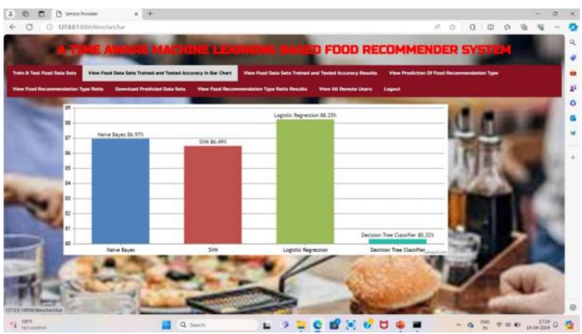
In this module, the admin can view the list of users who all registered. In this, the admin can view the user’s details such as, user name, email, address and admin authorize the users.

Remote User: -

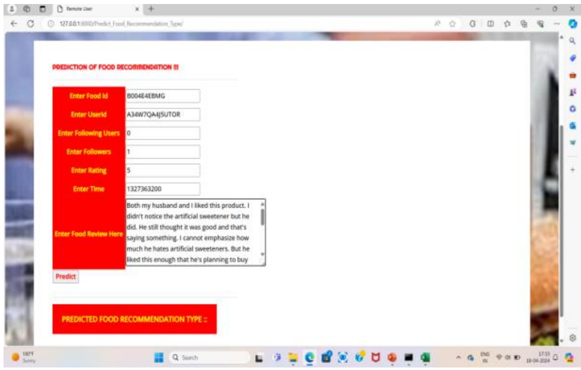
In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT FOOD RECOMMENDATION TYPE, VIEW YOUR PROFILE.

RESULT AND DISCUSSION

In above Screen is output of the Home Page.



In above Screen we got the Output of the Comparison Graph



In above Screen it is predicting.

CONCLUSION

In this paper, an SLR is conducted to track the most recent research advances in ensemble learning techniques for software defect prediction. This review is performed after critically analysing the most relevant research papers published in three well-known online libraries ACM, IEEE, Springer Link, and Science Direct. Five research questions regarding the different aspects of research progress on the use of ensemble learning techniques for software defect prediction are defined and addressed in this study. It is concluded that ensemble learning techniques performed significantly better than individual classifiers. In the future, a review of the effects of feature selection techniques on ensemble learning should be performed.

REFERENCES

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