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Implementation of Hybrid Recommender System using Machine Learning Techniques - A Review

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Introduction:

In the era of big data, generated data creates ample scope for both the customers and the business organizations. As organizations are supported by enormous data in every application domain, there is a scope for extracting knowledge from the data. Customers are in need of taking smarter decisions from the list of many choices available to them. The world is moving from the era of search to the era of discovery. If the customer does not know how to ask for the product while purchasing but finds them, then it is known as discovery. Search engines are also incorporating more innovative tools to fulfil the need of the customers as per their requirements. Query results may vary from user to user, depending upon the need. Handling the Information Overload problem with the aid of personalization is a challenge to support a win-win situation for both customers and the service providers.

Recommendation System (RecSys) [1] is a more ingenious information retrieval tool to handle Information Overload problems and personalization. It filters the required data as per the profile of the user to satisfy the need. Its objective is to extract intelligence from the data that satisfy the need of both service providers and customers. Customer satisfaction by getting the right product from a large collection increases the revenue of the business model.

Recommender systems are defined as a software tool that suggests the items and their features to the users. Earlier, the recommendations were made by the opinions of domain experts having vast amount of knowledge about the subject. As a result of immense growth indigital data in previous decades, the work of recommendation became stressful by using conventional knowledge base techniques. This enormous data lead to the development of software systems that recommend items precisely(Çano and Morisio, 2017).

The Recommender systems emerged as a necessary tool to assist users in accessing services from large sets of merchandise. Netflix provides movie recommendations, Amazon provides product recommendation services, Yahoo! recommends news, and Google gave recommendations of advertisements. Corporate organizations provide net services and recommendation ability together as functionality in the market(Song, Tekin and Van Der Schaar, 2016).

Machine Learning is considered as a sub domain of Artificial Intelligence that deals with the training skills of machine. The Algorithms of machine learning that typically used in the recommender systems are classified into two different categories namely Collaborative filtering and Content based filtering. The Collaborative method works on the interaction between the users and items. It mainly has an idea that people who agreed on previous interaction with the item are again going to like them in the future. The task of algorithms is to search out operation that predicts the utility of that past interaction. The various content- based strategies supports the similarities possess by things throughout their interactions(Isinkaye, Folajimi, & Ojokoh, 2015) .

There are various problems mentioned by the researchers in using the recommendation system strategies. The common issues mentioned are the Cold Start problem, Data sparsity problems, Accuracy problems, Diversity, and Scalability. Various researches were conducted with the help of machine learning to reduce the effectiveness of these challenges. These techniques still have a scope of extensions and futuristic measures that used to develop a better recommendation system(Song, Tekin and Van Der Schaar, 2016).

The author in this research compares various algorithms that previously used to overcome the mentioned problems and find out the various changes by comparing more contexts of data. The system investigates the machine learning algorithm that is best fitted to a given data. For better evaluation of large–scale contextual data, a hybrid approach that consists of various machine learning methods is proposed to provide more accuracy than the previously designedsystem.

Objectives:

In view of the motivation stated above, it is essential to design a Recommendation System using machine learning and deep learning approaches by considering hybrid features. In order to facilitate the foundation of this research work, the following objectives are derived.

- To design a classification model by emphasizing feature engineering.
- To design a regression model by considering various model-based features.
- To apply deep learning in predicting the likeness of the active users and recommending top-K items.
- To study the impact of the hybrid model.
- To apply machine learning techniques in different case studies of Recommendation System.
- To handle the challenging issues of Recommendation System such as cold start problem and Shilling attack.

Literature Review:

The core operation of any recommender system is to predict an item that may be found helpful by a user. The basis for the recommendation, however, varies from one recommender system to another. There exist several taxonomies to distinguish between different approaches to make a recommender system. Previously, the recommender system follows three basic approaches based on characteristic information and User item interactions. These techniques are Content-based filtering, Collaborative based filtering, and Hybrid filtering.

Asim A, Skander E. & R. kohli (2000) developed a Hierarchical Bayesian Recommendation system. The products for a recommendation in this system were new release and old release movies. The system, with the help of statistical methods based on customer ratings on products, was developed. Customized recommendations to the customers given with the help of a regression-based approach. The results show a better recommendation for the movie having higher ratings. The authors mentioned that for the recommendation of lower rating movies, this model was less desirable.

Gediminas Adomavicius, Bamshad Mobasher, Francesco Ricci & Alex Tuzhilin (2010) have given the concept of context in the recommender system. In their work, the authors mentioned the importance of contextual factors and change in them according to time. The authors also suggested the limitations of this system. The problem described in these systems was identifying which context is to be considered is still an area for studies. They also mentioned that the classification is only an initial and general high-level structure for characterizing the multi-faceted subject of contextual knowledge in recommendation systems. Linqi Song, Cem Tekin & Mihaela van der Schaar (2013) developed a recommender system algorithm based on the recommendation at the item cluster level. The authors mentioned various challenges like scalability, diversity, differential services, and cold start problems. This recommendation system worked on an associate algorithmic program that considers item preferences of users, which uses a square measure technique that supported their interaction with them. The authors in their system constructed an online item cluster tree and made a recommendation at the item-cluster level. They also introduced Adaptive Clustering Recommendation algorithm (ACR) for improving learning speed. This ACR technique is used to select adaptive cluster size giving balance to the recommendation and reducing cluster size. A comparison with another context-free algorithm has been made in this work. The limitations of this system occurred when this algorithm is used in a distributed manner.

Yao Lu, Sandy El Heou, Denis Gillet (2013) gave a hybrid recommender system for job seekers. They used a Content-based Similarity Computing and Ranking algorithm for the construction of the system. They used candidate, employer, and job fields and computed profile-based similarity and by using Personalized Multi-Relational Page Rank and indicated the importance of a particular page. The authors gave a better recommendation of this approach than previous approaches.

Negar Hariri, Bamshed Mobasher & Robin Burke (2014) have developed a system that adapts the contextual changes in interactive recommendations. The authors used the Multi-Arm Bandit algorithm and extended them to study the variation of the user's feedback due to contextual changes. If the change is noted, the algorithm based on Thompson sampling priorities the result. The algorithms prioritize the current context and depend on the user's feedback.

Maria R. Lee, Tsung Teng Chen & Ying Shun Chai (2016) have developed a Recommender System based on hybrid techniques using data from social networking sites for recommending Taiwan premiere movies. They have used Fb (API) to extract data from social media fan pages. The data preprocessing stage involves a collaborative filtering technique and applied multinomial logistic regression. They have evaluated results in two parts i.e., Cross-Validation and Online system questionnaire evaluation process. The accuracy is calculated for various genres, and the perception of users is rated by using the questionnaire evaluation process based online. This Recommender System is analyzed text only in traditional Chinese language, and experiments on other languages are not performed. Sufficient data on fan pages is required for the recommender system to work appropriately.

Agata Nawroka, Andrzej Kot & Marcin Nawrocki (2018) have studied various issues related to the application of Machine Learning in recommender systems. The study was conducted on data present in the Movie lens portal. The authors created algorithms that calculate

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prediction ratings. This algorithm was based on similarity if users and the objects. The errors that were considered in the prediction are RMSE and MAE, and the results show that these errors were less. The author mentioned that the system is effective only when a certain number of minimum ratings by users are considered.

Geetha G., Safa M., Fancy C., Saranya D. (2018) have developed a movie recommender system that was based on hybrid filtering for précised recommendation. The authors centered on the mix of the benefits of Content-based and collaborative based mostly filtering ways. The system allows the users to choose from the given set of attributes and then on the basis of the cumulative weight of attributes, and also, by using the k – mean algorithm, the system was able to recommend a list of movies. The system used only a small set of users that are based on an informal evaluation.

The work in the area of recommendation system based on the techniques of the Content base, Collaborative, and hybrid technologies. The algorithms used by authors commonly focused on the development of methods of more accuracy. More studies can achieve further exploration regarding overcoming the disadvantages like Cold – Start Problems, Scalability, sparsity problems, etc. These literature works give the base for experimentation with the help of Machine learning algorithms for achieving higher accuracy in recommender systems.

Proposed Framework System Architecture:

The System Architecture of Electricity Tariff Plan Recommendation System is depicted in Figure 1. The major Components of the models are as follows:

Infrastructure for generation to distribution: Electricity flow from the generating stations to the consumer is done through a transmission and distribution (T&D) system. Various generating companies sell and deliver energy via the T&D to the distributor. Distributors have various tariff plans in the categories like fixed plan (FG) or TOU (Time of use) plan.

Infrastructure for smart metering: In the power system deregulation model, users' energy usage and consumption are recorded by using smart meters. Users‟ energy usage pattern can be extracted from the smart meter infrastructure and associated with a suitable tariff plan.

Recommendation: The recommendation portion is represented in a dotted boundary line. It has two major components, as discussed below.

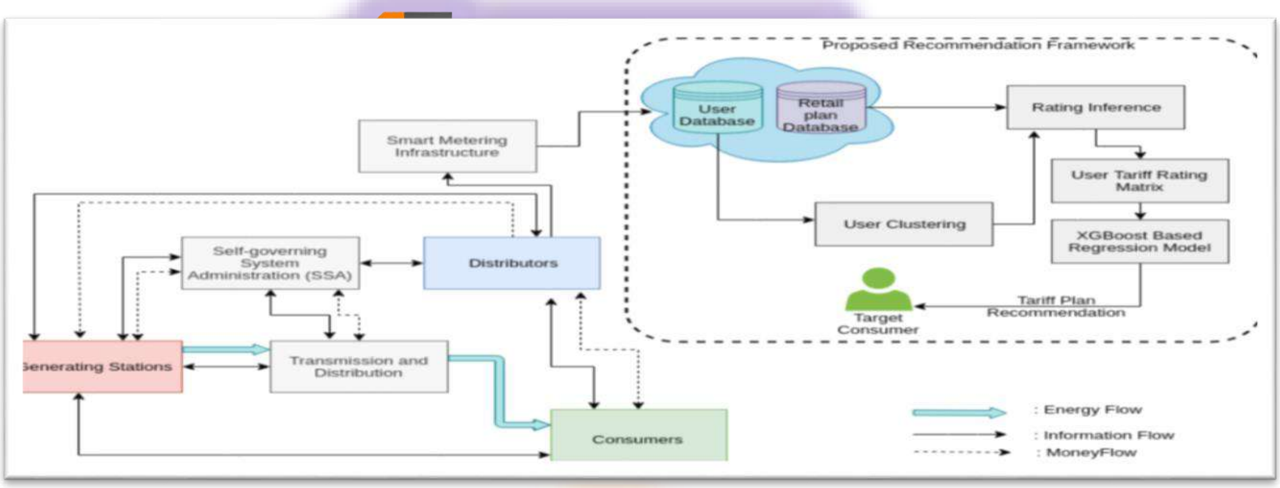

Figure 1: System Architecture of Tariff Plan Recommendation System

Conclusion:

This research work focused on designing a personalized Recommendation System using three machine learning approaches and successfully applied them to different real-world case studies. The performance of the Machine learning model heavily depends on features. In the Recommendation System, features can be generated from the explicit profile of the user or from another machine learning model. The hybrid model, which is a combination of more than one model can also be used to enhance the performance of the prediction. Similarly, feature generation can also be from more than one model. The objective of this work is to study the impact of both hybrid features and hybrid models.

In the first model, a classification model is used to predict the likeness of the user and top items from the predicted result can be recommended to the active user. As a case study, friend recommendation is designed using the classification model for the prediction of the unknown links in a social graph. Many graph-based features are used to facilitate better feature engineering. The State-of-the-art and cutting edge eXtream Gradient Boosting model is used to model the link prediction. It is seen that with proper feature engineering, the proposed model results in superior performance than other baseline classifiers.

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