Adaptive User Interface Design: A Case Study of Web Recommendation System

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***Abstract*—Personalization is another special form of adaptation where it widely implements in the development of recommendation system that gives adaptive web environment for users. The main concept of recommendation system is to obtain user behavior factor from user interest or search history and predict the next request as they visit web pages. There are some issues arise in recommender systems which they need a lot of data to efficiently build recommendations. Large amount of items and user data are best for getting good recommendations. In practice, however many challenges exist and evaluation results of recommendation systems has been mixed. This paper presents the case study of Netflix and other case studies in the development of recommendation system and analyzes some of the problems and challenges in implementing recommender systems.**

***Index Terms*—Adaptive User Interface; Recommendation System; Personalization.**

I. INTRODUCTION

Adaptive User Interface (AUI) has become vital role in personalize service because it changes to its user behavior and offers the information based on user requirements [1]. However, the complexity of software development nowadays can limit usability and can be a major cause of user frustration. This issue can be tackled with AUI by giving real-time contextual adaptation and the system can provide help with list of recommended actions that are particularly personalized for the user [2].

The role of user interface in recommendation system as a critical factor in effecting the characteristics for example general system usability, system acceptance, item rating behavior, selection behavior, trust, willingness to buy, willingness to reuse the recommendation systems, and willingness to promote the system to others [3].

Moreover, recommender system has developed an important tool for alleviating information overload for web users, which attempts to discover users' interest and make recommendation by learning the feedbacks of users' historical behavior [4]. It basically recognizes and delivers information based on user interest. After that, all the information data will be filtered and send relevant information to the users [5].

Recommender system is a form of personalization. Basically, the personalization happens gradually while it constructs and develops information about users interest, likes, dislikes, relevant and irrelevant information [6]. The system has been beneficial mostly to social and commerce sites. Static websites can turn into something interactive and meaningful to user experience using recommender system.

There are four filtering techniques in developing recommender system, which are demographic, content-based, knowledge-based and collaborative [7].

A. Demographic filtering

Demographic filtering is the basic technique in recommender system. Recommendations result produced by this system is too general and it is not scalable. This is because the recommender system is not adaptive if the user preferences change over time. Each user is classified based on their individual categories for instance age or gender. After that, the system delivers recommendation based on these demographic categories.

B. Content-based filtering

This algorithm will deliver recommend information based on user similar interest and liked in the past. The method used keywords to describe the elements and a user profile is built in order to specify the type of item of user likes.

C. Knowledge-based filtering

This method represents recommendation results based on user's needs and features of the item. Basically, this technique needs the user requirement and item to produce a list of suggestions.

D. Collaborative filtering

Collaborative filtering approach is the most popular techniques among all. It relies on the preference of items, which expressed by users. It can be seen in the form of ratings features. This method recommends items based on similar user preference.

To outline personalization approach in recommender system, the present study in section II provides an overview of the methods currently applied in recommendation system. After that the following sections discuss about the case study of Netflix in section III, which is our main reference. Other case studies in section IV, discussions and future works are described in section V and finally we conclude the paper in section VI.

II. RELATED WORKS

Irrelevant information and information overload can be confusing and frustrating. This is why recommender system is developed to solve this issue by filtering out information based on user needs. There are different types of approaches and techniques for building recommendations systems, which can utilize collaborative filtering, content-based filtering, knowledge-based filtering and demographic filtering.

Bruno Pradel et al. [8] presented an experimental evaluation of several collaborative filtering systems on real-life purchase dataset. The system contains purchase history information from users. Their results show that recommender system is best applied on purchase compare to rating data. However, rating data [9] is very important to new user. If new users ignore the rating feature, the recommender system cannot provide personalized recommendation based on the memory-based collaborative filtering which is one of the technique in collaborative filtering.

Replication of relevant information is one of the main issues in filtering information. S. Saravanan [10] has designed content-based recommendation algorithms. The algorithm contains two approaches, which are removing the similar information and generating the best recommendation for user.

Vala A. Rohani et. al [11] enhancing content-based recommender system for academic social networks (ECSN algorithm). The experiment is performed by comparing different types of approaches in order to test the effectiveness. It shows that ECSN algorithm effectively improved the performance of prediction accuracy compared to other approaches.

A. L. Garrido et al. [12] developed a mobile phone application by implementing Knowledge-based Geographical News Recommender (KGNR) approach. User profile and user geolocation generate personalized news recommendation by combining Natural Language Processing (NLP) techniques, ontologies and classic recommendation methods.

Cold-start has become major challenges in recommender system area. However, this problem can be resolved by utilizing the best possible large amount of current ratings from current users [13]. Safoury et al. [14] introduced a solution for the cold-start problem by utilizing the demographic data of the new user instead of their ratings. This allowed the system to assist the users even they had no ratings yet.

In previous work, certain novel approaches have been incorporated in the recommender systems that leads to development of an adaptive personalize recommender systems. There are different types of techniques in recommender systems, however the most essential element in developing effective wide-ranging recommendation system is to indicate suitable conceptual design approach that is capable of running complex machine learning algorithms. Great analytics is another important feature in recommendation system in order to obtain the best recommendation engine.

III. NETFLIX: A CASE STUDY [15]

Netflix is the most popular recommender systems, which it is a streaming service that allows viewers to watch a wide variety of movies, dramas, documentaries and many more. The applications allow users to browse catalog that contains variety of TV shows and movies options so that users can watch the videos available at any time on any device. This case study offers a high-level reference for developing recommender systems

A. *Recommendation System*

Recommender system in Netflix aim to control a group of people for example family that has different interest, hence everyone in a household can use same membership. Netflix has provided the Top 10 row features that contain different types of movies, which determine subject for anyone in the group or as a whole group.

Basically, Netflix target subscriptions market to families, which a person with different interest can share a single account. The system allows members to create up to 5 different profiles in one account. The best thing is it can personalize the user knowledge for each profile that has created by the user.

This application also highlights awareness in Netflix personalization. The system wants user to be aware of how the system is adapting to their interests. The reason why of the awareness is the system wants to urge users to respond and provide some feedback in order to obtain improved recommendations. An appropriate description is one of the method to build trust on why the system choose to recommend a given movie or drama.

B. *System Architecture*

A generic three-layer architecture is implemented in Netflix to address complex task such as handling large amount of current data, responsive to user interactions and flexible experiment with new recommendation approach. The general system architecture of Netflix system recommendation is shown in Figure 1.

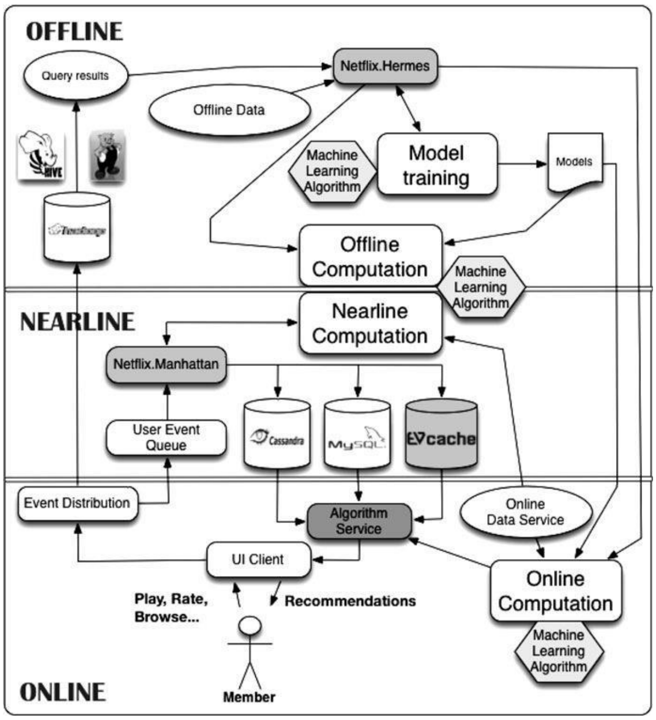

Figure 1: System-level architecture diagram for a recommendation system. The main components of the architecture contain one or more machine learning algorithms. [15]

The system architecture illustrates a several personalization in algorithm services, which consist of ranking, row selection and ratings prediction. Each of these features requires recommendations that involve multi-layered machine learning. Basically, users make most of the information based on their interest that will deliver to the system. After that the system will generate a list of recommendations to the user.

Based on Figure 1, the system architecture consists of three different types of computation processes which are *offline, nearline* and *online. Offline* is a process where it has fewer control on the amount of data and also less limitation in the computational complexity of the algorithms.

Online computation process clearly can respond well to current events and user interaction. However, it has to respond to user requirement in real-time. The computational complexity of algorithms can be limited as well as the amount of data that can be processed.

Lastly, *nearline* process can perform online types of computations but do not involve in real-time. In addition, *model training* in the system architecture is another method of computation that uses existing data to produce a model that will be used during the real computation of recommendation results.

One of the issues that arise in personalization architecture is how to combine and accomplish the two computations process, which is *online* and *offline* in a seamless method.

C. Adaptive User Interface

Netflix is all about personalization including user interface. The website uses a two-dimensional layout on their homepage in order to make navigation easy and efficient. The horizontal side is where user can scroll it to see more videos. User also can see more rows or themes on the vertical side. The rows update based on user's actions in real-time that can change the video recommendation.

Some of the features that can personalize by customer based on their needs are subtitle appearance (font size and color) and My List category which user can inquire the system to stop adding more suggestions. Another features personalization is parents can set the homepage to kids profile in manage profile menu. Basically, kids are unable to view adult content.

Another great thing about personalization in Netflix is the homepage. Personalize homepage in Netflix is to give user full experience using the website. Fundamentally user needs to fill out a simple questionnaire about different genre movies or TV shows to get user taste preferences. After that a personalized homepage that contain list of recommendations is generated by the system.

IV. OTHER CASE STUDIES

Many Internet companies that have numerous applications areas use recommendation systems. Each domain has its own unique recommendation challenges and approach in order to develop the best recommendation system to user. In particular the following case studies were chosen to show how inclusive recommender system can be put into practice effectively and developing system that user friendly and meet user requirements.

A. StitchFix

Most largest commerce sites and application use recommender systems to provide their customer with good user experience and interaction. An online clothing company called Stitch Fix applies machine learning algorithm and human processing in their recommendation system. Basically, it uses both stylist expertise and algorithm to obtain data for recommender system.

According to Eric Colson [16], the Chief Algorithms Officer at Stitch Fix Data Science, expert-human processing is used to perform several tasks deemed outside the purview of machines. While machines do their processing under the assumption of item-independence, human processing is used to synthesize concepts from the individual items to create a curated set that collectively represent better relevance versus the sum of the individual relevancy scores.

However, the significant of AUI design in recommender system is not including in Stitch Fix. User can experience the adaptation in terms of content where all data that given by user will deliver to the system. After that recommendation list will appear based on user interest.

B. Spotify

Spotify is a music, podcast and video streaming service which user can personalize their own playlist and share it to other users and also social media. The great thing about Spotify is it generates Discover Weekly feature, which has a list of music recommendations. There are over 2 billion playlist that created by users and it is not just about individual interest. The Discover Weekly is also about other people interest.

In terms of adaptive user interface design, Spotify do not have the customizable user interface and lack the ability to change some of the layout features.

C. Amazon

Another e-commerce website that applied recommendation algorithms is Amazon.com. The website is an online store that personalizes users based on their interests. The system store large amount of data and it has very good recommendation algorithm that is scalable to large data sources. It produces online recommendations quickly when information changes in user's data.

The algorithm development process contains item-to-item collaborative filtering, scalable large data and generates good list of recommendations in real time [17].

The user interface in Amazon.com is all about user personalization. The system learns the buying pattern of the user by using the cookies search of the user. The homepage layout is customizes based on user previous interaction. Making good use of data is imperative in Amazon to designing great-customized user experiences.

Another AUI elements in Amazon are links and banners for advertisement. The system allows user to add some of the features to advertise products in the website. It also provides the product link tools, which let user to build customized text, links and image links to products.

D. Summary

In previous work, certain novel approaches have been incorporated in the recommender systems that leads to development of an adaptive personalize recommender systems. However, some of them lack of scalability, which is the process cannot handle large amount of data and also lack of AUI elements which is the main criterion in this research.

Netflix and Amazon have evolving an amazing development in recommendation system. Furthermore, these websites want user to have full experience by embracing the AUI aspects such as personalization in layout, font appearances and navigation.

On the other hand, StitchFix and Spotify is only focusing personalize in recommender system. These websites do not have personalization in terms of AUI which user cannot personalize layout or other elements in AUI and it is not alterable. However, users can receive list of recommendations based on their interest and search history.

The related works of the approaches is combined and presented in Table 1.

Table1
Aggregated evaluation.

	AUI	User Feedback	Scalability	Personalize recommendations of content
Netflix	√	√	√	√
StitchFix	●	√	●	√
Spotify	●	√	√	√
Amazon	√	√	√	√

√ Fulfills Criterion
● Does not Fulfill Criterion / not applicable

V. DISCUSSIONS AND FUTURE WORKS

Quite extensive research has been done in the development of recommender system in view of its importance in making information retrieval successful to user. In present work, certain novel features have been incorporated in the adaptation recommender system that makes the system efficient task and satisfying.

Netflix has become the most competence content discovery in recommendation system algorithm, as the on-demand streaming video is very high. It has functioned successfully to make sure its recommendation algorithms can emphasize most of its content library as possible. To become global recommendation system is what they aim for. Clearly, Netflix is aware that the global approach will be the main goal to becoming a huge success in their system.

Despite its well-known recommendation system, it is good if the system extends their AUI content to be more competent and satisfaction to user since their goal is to develop global approach in recommendation system. This will be research opportunity to expand on how element in AUI can integrate in the development of recommendation system in order to go beyond user satisfaction.

VI. CONCLUSION

The Internet stores a wide-ranging of information resources and the number of choices is overwhelming. Therefore, information retrieval and filtering is very important to alleviate the overload information. Recommender system solves this problem by examining through large capacity of data in order to deliver user with personalized information and assistances.

In this paper, we have discussed about previous study and the system architecture of web recommendation system in the case study of Netflix and also other case studies that applies recommender algorithm in their system. We hope that the development of AUI can be implemented in recommendation system to make it more proficient and we strongly belief that some of extensions works could be done in this area.

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