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# Understanding Personalization of Recommender System: A Domain Perspective

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**Abstract**

The abundance of information paved the way for personalization of web information retrieval systems in order to garner the attention of the web users. With an inclination towards customer oriented service, the online systems render recommendations to provide items of interest to the web user. Personalization in recommendation systems is achieved by creation of custom alternatives for delivering the right experience to the right user at the right time through the right device. Domain relevant personalization is the need of the hour and research in recommendation system is towards identifying the domain specific characteristics for providing more accurate recommendations. This research article provides an overview of various domain adaptation strategies incorporated and practiced in the recommendation system literature. The article focus on domain based personal agents in the prior research of the recommendation system for the domain of music, video, product sale, tourism, social network, news, E-learning and restaurant.

**Keywords:** Recommender Systems, Personalization, Domain

## INTRODUCTION

In recent years, the world has seen the explosive growth of information in the form of web services. The huge growth of information is impeding the web information retrieval systems to get the maximum attention of the web users. The web user attention on the screen is short, and one of the major achievements of any website is getting the attention of web users who are facing the information explosion [1] [2]. One of the ways to influence the users is personalizing the content on the webpage. Personalization is the provision to the individual with tailored products, services or information [3]. Organizations have long personalized their websites for customer segments, and with an inclination towards customer oriented service, there is a need to understand the customers for providing products/services of interest and hence, recommender systems have become popular both commercially and in the research community.

Recommender system adds value both to the provider and the consumer. In the web based service environment like online shops, movie rental, news and E-learning, the provider gives personalized service to the consumer, increase his/her trust and also persuade and promote products using recommender systems. The recommender system helps the consumer to narrow down his/her set of choices from the abundant list and also help in discovering new items of interest. The two basic entities of any recommender system are items, which are the product / services, and users, who are procuring those products / services. These basic entities of the recommender system are represented as a user-item matrix, a tensor or a graph.

The recommender system employs the filtering mechanisms to provide the item of interest to the user. The filtering techniques used in recommender systems are based on: the knowledge-base - the prior information that the system has about the item/user; the input data - the information about the preference of item/user communicated to the recommender system that assist in generating recommendations; and the algorithm - combines the prior knowledge and the input data to arrive at the recommendation list for a specific user. The various filtering techniques used by recommender systems are: Content Based - the user profile is matched with item description to make recommendation; Collaborative Filter Based - similar items/users are grouped, and based on the 'wisdom of crowd', items are recommended to users; Context Aware - dynamically assess the user needs based on the context to provide item of interest. Context is a multi faceted concept which refers to conditions that characterizes the identities and attributes of people and devices, the locations of people and devices, the activities of the people, and also the roles and intentions of people when participating in the activities; Hybrid – combines more than one of the above mentioned methods to provide recommendation.

The remainder of the article is organized as follows: Section 2 describes domain based personalization of the recommendation system for the domain of music, video, product sale, tourism, social network, news, E-learning and restaurant. Section 3 provides the conclusion.

## RECOMMENDER SYSTEM: PERSONALIZATION

Personalization in recommender system is the creation of custom alternatives that meets the individual customer's preferences based on the human behaviour and the domain knowledge [4]. Human behaviour is defined as "the potential and expressed capacity for physical, mental and social activity during the phases of human life" and by definition, domain knowledge is the knowledge specific to a "particular field of thought, activity or interest especially one over which someone has control, influence or rights". The human behavioural inclination to the domain varies. Personalization in recommender systems is achieved by delivering relevant, tailored experience to the right user at the right time on the right device meeting the individual user needs by combining historical, behavioural and profile data with real-time situational feedback and there by exploiting recommenders as a personalization tool tailoring products / services of interest to the users.

Recommenders also assist and augment the process of making the choices between the alternatives when an individual does not have sufficient experience in making the choice. Concept based human understanding of categorizing of items with respect to the domain and combining the domain based personal agents in the recommender techniques is essential to make appropriate recommendation [5]. Hence knowledge specific to the domain is incorporated with the design of the recommendation system for a personalized user experience. A comprehensive review of the various domain adaptation methods incorporated in the prior research of the recommendation system is presented for the domain of music, video, product sale, tourism, social network, news, E-learning and restaurant.

### Music Domain

Music is an art with elements such as pitch, dynamics, intensity, rhythm, structures as contrast, repetition and continuity. Online music is available as downloadable audio files or as audio streams. Users listen to music that fit their taste, preference and context. With abounding number of digital music available, music recommendation plays a vital role in providing relevant music to users. Human emotion influences music listening and music elicits emotional responses from listeners [6] [7]. The emotion transition model of listeners is constructed for generating dynamic playlist to listeners [8].

The unique characteristic of music listeners is that they often repeat their favourite songs, and music recommendation system exploits this characteristic to identify and increase the occurrence of those songs in the recommendation list [9]. The repeated occurrence of the songs may be the same pattern of music (polysemy) or the same song (synonymy). Listener's preference with the mood, location, time and event in daily life influences the choice of music and a context based ontology helps in matching the music with the context for providing relevant recommendation [10]. The songs repeat in the recommendation list based on the mood, location, time and event in daily life. In today's virtual social environment, social tagging is an important source for information retrieval system. Alexandros et al. proposed a cubic correlation between users, tags, and items for music recommendation system [11].

### Video Domain

The ubiquitous availability of internet and the natural human inclination for entertainment is making online video on-demand service such as Netflix, Amazon-Prime, a popular business. The recommendation system for such services is deployed as a business tool for helping the customers with the preference list of videos. It also helps the providers in maximizing their profit by evoking continuous watching of videos [12]. Recommendation system as a business promotional tool is designed with balanced characteristics to prevent customers from abandonment of service to an alternate video service provider. Emotions also influence a user's choice of video content [13]. The choice of a user watching a particular video depends on the mood, location, time, event and the companion. A hybrid distributed framework of an online-offline recommendation system using diffusion principle, in which the offline learning reduces the working limits of the online learning algorithm, provides an incremental and scalable system [14].

Recommendation system uses the detected emotion to rationally select videos for the users. Any information system assesses emotions either explicitly or implicitly [15]. Emotions of the user are explicitly assessed using emoticons or questionnaires where as implicit assessment is done using video cameras, speech recognition etc. Affective recommendation systems using emotion detection enhance the user experience by adding user centric features to the mechanized database approaches [16].

Similar to the phenomenon prevailing in music listeners, the movie watchers, especially children enjoy watching the same video content more than once, though, usually video watching is novelty driven. The video recommendation system also exploits continuity in videos watching in case of episodes of online TV shows and movie sequels [17]. The recommendation system implemented in video streaming websites such as YouTube scales dynamically since millions of users upload and watch videos every second. A recommendation system for such a web application has sophisticated mechanism for scaling and freshness [18]. Context matters in video recommendation: What to recommend? When to recommend? Whom to recommend? The factors such as place, time and companionship have an immense influence on the choice of the video and hence must be considered for recommendation [19].

### Product Domain

Product recommendations in E-commerce websites improve sales by converting browsers to buyers, by suggesting cross-selling of additional products to a purchase and also by creating value added relationship with the customer [20].A software product line has managed set of features that satisfies the specific need of a particular market segment. Recommendation system used in E-commerce websites target a particular market segment using their set of unique features and the product line feature knowledge imbibed recommendations enable fast market entry, flexible response and adaptable personalization [21].

Recommendation system is a one-to-one online marketing tool in which a particular event (search option) triggered by the customer facilitates the system to provide a list of relevant items which are in the scope of the purchase [22]. In the E-commerce domain, the customer details such as gender, age, marital status, number of children and monetary status determine the purchase of the products. Customers relative spending on different product lines provide effective mechanism for recommendation algorithm to be used as a target marketing tool [23]. The system implicitly gathers information of the products added to the cart, the frequency of purchase of the product and the price of the purchased product to determine relevant products for recommendation to a user [24]. The temporal association among the items in the cart is an important criterion for future recommendations [25].

**Tourism Domain**

Advances in information and communication technology are promoting the tourism industry by providing the tourists with access to inexpensive, accurate, reliable information about restaurants, hotels, and tourist attractions. The online tourist information system exploits the high degree of temporal and spatial regularity in human mobility patterns [26]. On a broader scope, the human behaviour is regular and predictable [27]. The predictability of human mobility and behaviour is used to create personalized model for recommendation based on behavioural patterns. The geographical distance a person would travel from the 'place-of-stay' is same and hence where ever that person travels, the 'places-to-visit' recommended must be within the geographical distance. The inherent similarity in the travel patterns is used in 'places-to-visit' / 'things-to-do' recommendations for the mobile users with relevance to their current context.

Location plays a significant role in users' check-in behaviour to a point of interest. Location based grouping of users provide active user classification for recommending relevant point of interest [28]. The correlation between users in the location based social network (LSBN) helps in filtering potential locations for recommendation [29]. Point of interest recommendation is personalized by incorporating user preference information with location aware services provided by LSBNs [30]. The geographical influence on location (i.e.) the proximity between the points of interest is exploited to provide point of interest recommendations to users [31]. Another important characteristic of the tourism domain is that people travel with one or more persons. Hence considering the heterogeneous preferences of the tourist group tailors the recommendation of the tourist attraction generic to the group [32].

**Social Network Domain**

Traditionally, in real life, friends are influenced by geographical distance between each other. In this virtual age, people connect with others based on life style, social status, moral values, personal attitude and existing social relations [33]. These characteristics are pondered in designing friend recommendation in social networks. Zhibo et al. exploited the user life style information extracted from smart phone sensors for friend recommendation [34].

The semantic structure of social tags derives similar attitude persons and the topological structure of the user's social network derives the existing social relations for friend recommendation [35]. The personal attitude of users is derived from the content postings and the existing relationships in the social network. The derived personal attitude helps in recommending new friends [36]. The virtual social network helps in developing effective real world interactions. The similarity in the places visited and the geographical nearness extracts like-minded people in joining hand for organizing or participating a real community event [37].

**News Domain**

In this digital era, scrolling through a tablet is much easier than reading a newspaper. Each new event has a 24 hour news cycle and it has to be delivered in a compelling manner to stay ahead of the competitors. News recommendation must filter the news considering the 24-hour cycle. The volume of online news doubles every year along with the users [38]. Personalized news displaying helps to keep the users hooked on to online news portals. The prediction of the next news read by the user is an important criterion in the news domain recommendation [39]. The time sequence characteristic of the user behaviour is exploited for news recommendation.

The contextual information obtained from implicit feedback such as the time of day, the age of a read news article and the time spent with the news article helps to grapple with the dynamic nature of the news recommendation [40]. The news domain timeliness and the concept drift phenomenon require recommendation algorithms to update its recommendation list on recency and popularity of the news on a regular and reliable basis [41]. Lei et al. exploited the short shelf life, the reading time sequence characteristic of news article and the news locality for implementing topic models for news recommendation [42].

**E-learning Domain**

Online web based learning potentially renders real time collaboration and instant interactivity regardless of time or location [43]. The adaptive E-learning environment determines "what" and "when" to deliver the learning materials [44]. The learning style and the domain level knowledge determine the user preference of the learning objects (documents, video lectures). Learner's historical sequential learning pattern collected from their interaction with the system helps for resource pre-fetching in the learning environment [45]. A sustained meaningful learning relationship is achieved by adaptive sequencing of the courseware [46].

Smart learning environment customizes the learning path of the learners. Learning object navigation guidance enhances the learner's learning achievement [47]. The accuracy and correctness of the learning object encourages learners to systematically construct their personal knowledge [48]. Standardized courseware recommendation with appropriate learning assistance sustains learners with a particular online web based learning platform. Memory retention is unique to an individual and based on the individual's learning memory cycle, learning objects which are recommended to users [49]. Soulef et al. designed a personalized recommendation system by profiling the learner's knowledge level and memory capacity [50].

### Restaurant Domain

Usually, people decide to dine at the nick of the time and recommendation system provides users with suitable, affordable and easily accessible restaurants. Hence the context information such as the place and the time of search is exploited to render the restaurant recommendation service [51]. The features of the recommended restaurant exhibit the user preference in the past [52]. The similarity in the dining experience, the price factor and the type of cuisine is also proved effective in restaurant recommendation [53].

A visualized representation of the location of the restaurant and the approach to the restaurant is an added feature of the recommendation service. Human innate nature in exploration is dominant in his dining behaviour. The novelty seeking tendency is analyzed from the historical visited restaurants to provide the recommendation [54]. The recommendation of items in the restaurant menu considering the health specification of the customer and the environment condition enables personalized well-being care for the individual [55]. Restaurant recommendation should consider the preference of more than a single person when a group of persons needed the service together. A multi criteria model with each criterion representing the preference of an individual in the group is required for recommending a restaurant for a group of users [56]. Table 1 summarizes the domain, filtering type, and the domain characteristic used in the recommender system.

**Table 1.** Summary of domain characteristics used in RS

| Domain | Filtering Type | Domain Characteristic |
|---|---|---|
| Music | Content Based, Collaborative, Context Based | Polysemy, Synonymy, Repetition of music, Listener's emotion, Time, Location and Event |
| Video | Content Based, Collaborative, Context Based, Hybrid | Scaling and freshness of online streaming videos, Movie Sequel, Business value, Targeted marketing tool, User's emotion, Time, Location and Companion |
| Product | Collaborative, Hybrid | Fast growing number of customers and products, Fast growing number of customers and products, Products purchased together, Frequently purchased products, Economics, Frequency and Price of products. |
| Tourism | Content Based, Collaborative, Context Based | People travel in groups, Location centric, "word of mouth" influence, Relatedness of near geographical location, Regularity in human mobility. |
| Social Network | Content Based, Collaborative, Context Based | Attitude, Taste, Lifestyle, Geographical nearness, Recency, Popularity |
| News | Collaborative, Context Based, Hybrid | Volume, Volatility, Short shelf life, Reading time sequence characteristics of news article, News locality, Reading time, Age of the news article, Reading time sequence characteristics of articles. |
| E-learning | Content Based, Context Based, Hybrid | Learner memory capacity, Learning style, Learner's knowledge level, Dynamic sequencing of learning material, Ubiquitousness, Learner's knowledge level, Learner memory capacity. |
| Restaurant | Context Based, Hybrid | Weather condition, Companion, Novelty, Personal well-being, Time constraint |

## CONCLUSION

The survey provides an overview of domain adaptation strategies exploited in the prior research for creating custom alternatives in providing a list of relevant items to the web users in the recommendation system. A detailed literature survey of the user and item characteristics in rendering domain specific recommendation is presented for the domain of music, video, product sale, tourism, social network, news, E-learning and restaurant. The user and the item characteristics pertaining to the domain helps in rendering domain specific recommendation. Therefore, the online recommendation application must incorporate domain concepts for effective personalization.

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