

An appraisal on the methods and techniques of recommender models for personalised marketing campaigns

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Abstract. Recommender models for personalized marketing empower businesses to provide personalized recommendations of goods or services to customers to fulfil their requirements, thus ultimately improves the customer buying experience. Various recommender models powered by robust machine learning algorithms were reviewed on the methods and techniques to appraise its performance concerning the personalized marketing campaigns. Recommender models can be broadly categorized into four types such as content-based, collaborative-based, knowledge-based and hybrid-based. The content-based recommendation is suitable when the system, user or product is new where classification and regression algorithms are mostly implemented. The collaborative-based recommendation is suitable when a more accurate prediction is required where Neighbour-based models, Bayesian methods, rule-based models, decision trees, and latent matrix factorization models may be implemented in this scenario. Knowledge-based recommenders are well suited for recommendations that address explicitly defined user requirements. Different types of recommenders use different sources of data and inherently have different strengths and weaknesses. Selecting the suitable recommender model with the consideration of the scenario and domain of application is very crucial. Therefore, an in-depth research is required and done on the emphasis of the application of recommender models in the personalized marketing especially on the hybrid models with a more efficient deployment for mass applications in this contemporary data-driven business world.

Index Terms. machine learning, personalized marketing, recommender models, predictive models, content filtering, collaborative filtering.

1. Introduction

The concept of personalized marketing was derived from one to one marketing campaigns tailored by businesses which leverage on data-driven decision making, thus greatly aided to deliver individualized marketing communication and product offerings to existing, potential and prospective customers, regardless of the channel [1], [2], [3]. According to the Monetate Personalization Pyramid as shown in Figure 1, mass personalization through segmentation can be achieved by identifying groups with similar patterns, based on customer demographic, geographic, psychographic and psychological characteristics, social influence, market place and consumption behaviour [4]. The operations of



personalized marketing have demonstrated increasing sales & basket size, improved customer loyalty, and enhanced customer experience [3]. The personalization can reach up to an individual level through data collection, and analysis with the advancement of computational power, machine learning and automation.

The recommender models are important and widely used business intelligence support engine empowered by robust machine learning algorithms to offer personalized marketing suggestions and recommendations to customers. The prime function of the machine learning algorithm is to learn the customers' purchase behaviour towards the goods & services and predict more suitable recommendations for their future purchases. This is done by profiling each customer based on extreme segmentations where the minimum size of the target segment is one person [3]. This operation would aid the businesses to plan and execute marketing campaigns in a more personalized manner. Targeted emails, custom video messages, product recommendations, social media targeted advertisement and so on are some of the classic examples of successful personalized marketing. Amazon, YouTube and Spotify are some of the businesses that enjoy the benefits of these recommender models for personalized marketing.

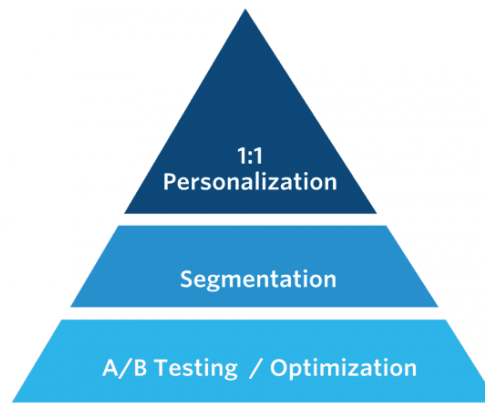


Fig. 1. Monetate Personalization Pyramid [4]

There are various approaches to developing recommender models with multiple variations as proposed in the literature. The suitability of the recommender model mainly depends on the objective that the business is striving to achieve [5]. This possesses difficulties in choosing a suitable machine learning algorithm that fits the need. However, the dynamic aspects like rising customer expectations, purchasing behaviour and preferences always demand the businesses to treat the customers exclusively and to satisfy their requirements [3]. It has been very clearly understood that every customer prefers to have a personalized communication from the businesses.

This personalization would be much more difficult if it is to be done manually. Therefore, automated recommender models would ease the marketing communication and reach the customer more effectively. This paper offers a valuable appraisal on the techniques, methods and the applications of recommender models along with the relevant machine learning algorithms used in personalization in the business domain.

2. Recommender models

2.1. Categories of recommender models

Recommender models mainly rely on two types of information such as characteristic information and user-item interactions [6], [7], [8]. The characteristic information includes facts about the items (for

example categories, descriptions, functionality), and the customers, also known as users (for examples their preferences, profiles, location). Similarly, the user-item interactions information includes ratings, likes, buying and browsing behaviour. Based on this, four key techniques with relevant algorithms are used in building recommender models namely content-based filtering, collaborative-based filtering, knowledge based and a hybrid models [6], [9], [10], [11], [12]. The conceptual goal and the input of each approach are summarized in Table 1 for a better understanding.

Table 1. The concept goals and input of various recommender systems [5]

Approach	Conceptual goal	Input
Collaborative-based	The recommendations are given based on collaborative approach and leverages the ratings and actions of the users	User and community rating
Content-based	The recommendations are given based on the contents (attributes) favoured in the past rating and actions	User rating and item attributes
Knowledge-based	The recommendations are given based on the explicit specification of the kind of contents (attributes) that are wanted	User specifications, item attributes and domain knowledge

2.1.1. Content-based

Content based focuses on the attributes that describe the items that are to be recommended. In this method, the user's purchasing behaviour and preferences are combined with the item metadata such as the genre, characteristics and size to make a personalized recommendation [6], [10]. This type of recommender models is advantageous when a system, user or item is new where no rating history is available, thus commonly known as 'cold start'. The recommendations are easily acquired through the analysis of initial clicks, or specified preferences, however, is dependent on the quality of the data and may not be as accurate as of the collaborative based method [13]. The model has a limited capability to expand the recommendations to other areas that may be of interest to the user as it is based on the existing preference [6], [14].

2.1.2. Collaborative-based

Collaborative based models rely on the integrations between user and items [6], [10], [15]. User-based filtering is the technique deployed by finding users those have similar historical purchasing, browsing history or preferences, and therefore are more likely to be purchasing similar items in the future. This enables personalized marketing to be deployed via effective predictions based on historical data. The familiarity of the domain knowledge is not required in making a recommendation using the collaborative based technique but considered as one of the prime advantages [16]. It is particularly useful when the analysis of the content is difficult to automate such as image, audio or video. The collaborative based technique can help in discovering new interests based on similar user behaviour or purchase behaviour [6], [10], [14]. Furthermore, the collaborative based technique poses a big challenge in cold starts, where the issue of sparsity will occur when there is a low number of ratings for a large corpus of items, thus insufficient to establish accurate correlations [12], [16], [17]. However prime E-Commerce players were able to do it successfully based on millions of historical purchase and user data.

2.1.3. Knowledge-based

Knowledge-based recommender models are applicable when the users willingly select their preferences that match the item description. This type of recommender models does not use ratings and is suitable for recommendations of items that are rarely purchased and seldom rated like real estate, stock, or expensive goods [6], [18], [19]. This technique is also suitable for cold-start situations, or when a user's preference evolves over time. On the other hand, the results of this model could sometimes be obvious as it does not utilise the historical community-based user ratings [6].

2.1.4. Hybrid-based

The hybrid recommender models combine the use of multiple data sources or various types of recommender models to leverage on its strength for difference scenarios [20]. This would consider the content-based and/or collaborative-based and/or knowledge-based recommender models to build, thus try to produce an effective result.

2.2. Machine Learning Algorithms

This section discusses the types of machine learning algorithms applied in recommender model building. The machine learning algorithms are the core of these recommender models which does close predictions.

2.2.1. Content-based models

In a content-based recommender model, firstly, the discriminative features of the item are extracted and converted into a vector of keywords by applying standard natural language processing techniques [10]. According to reference [10], the importance of the keywords can be represented either by referring the weight of the keywords using TF-IDF (Term Frequency-Inverse Document Frequency) technique or by the importance of the domain that the keyword represents. For example, the title and actor domain may be given higher importance than a movie synopsis. Then, the similarity of one item to another is calculated using Cosine Similarity, Euclidean distance or Pearson's Correlation between the vectors of the items to make the most suitable recommendation.

2.2.2. Collaborative-based models

Two common algorithms such as memory-based and model-based are generally used to build collaborative-based recommender models [6]. The memory-based method is one of the earliest collaborative-based algorithms used and also known as neighbourhood-based algorithms. This method tries to predict the user ratings of an item based on the correlation of similarity between their neighbors as shown in Fig. 2. Memory-based collaborative techniques can be either user-based or item-based. The user-based technique uses the rating history of a similar cluster of users for example as A to make the recommendation for B as shown in Fig. 3. However, the item-based collaborative technique predicts items that A will purchase based on the similarity to the item B of which A has purchased or liked as displayed in Fig. 4. Memory-based techniques are simple to implement and easy to explain. However, it does not predict well when the rating is sparse.

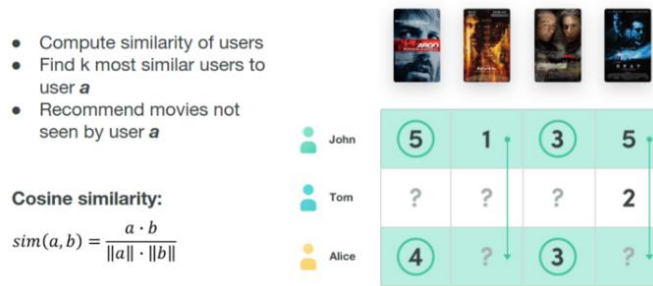


Fig. 2. k-nearest neighbor using cosine similarity [21]

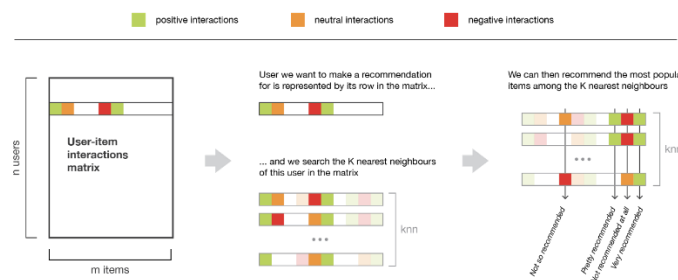


Fig. 3. User-based collaborative filtering [8]

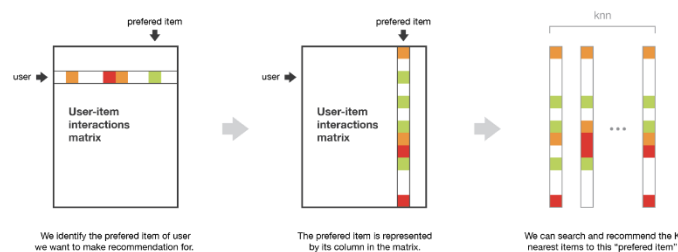


Fig. 4. Item-based collaborative filtering [8]

In a model-based technique, the machine learning algorithms are utilized to develop a prediction model based on the attributes available in the framework. Out of 26 research articles on recommender models that were reviewed by reference [22], the Bayesian and decision tree are the top two machine learning algorithms used probably due to their simplicity as presented in Table 2. The popularity is followed by matrix factorization, neighbour-based, neural network and rule learning. The neural network algorithm seems promising, however further studies is to be conducted to understand its black box approach. The authors noticed that two other machine learning algorithms have also been widely studied in recent years which were the Bandit algorithms and ensemble or hybrid approaches. However, both algorithms have high complexity which may impede its adoption.

Table 2. Types of machine learning algorithms used in recommender systems [adapted from 22]

Category	Total
Bayesian	7
Decision Tree	5
Matrix factorization-based	4
Neighbor-based	4
Neural Network	4
Rule Learning	4
Ensemble	3
Gradient descent-based	3
Kernel methods	3
Clustering	2
Associative classification	1
Bandit	1
Lazy learning	1
Regularization methods	1
Topic Independent Scoring Algorithm	1

As depicted in Fig. 5, the latent matrix factorization method has a significant level of prediction even in the case of sparse rating matrices. The algorithm minimizes the dimensionality of the matrix of user and items by creating two or more small matrices with latent components where the application of principal component analysis can be used to reduce the number of dimensions. This method dominates the research in various recommender models due to its simplicity and its significant performance.

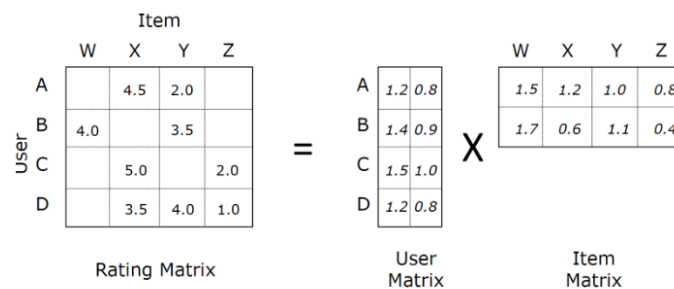


Fig. 5. Matrix Factorization [23]

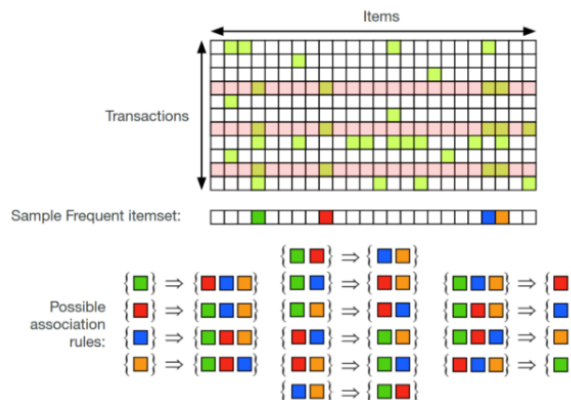


Fig. 6. Associative Classification [7]

As portrayed in Fig. 6, another type of model-based algorithm is the associative classification which identifies the relationships among the items by studying the patterns of co-occurrence between the transactions [24].

2.2.3. Knowledge-based models

In knowledge-based recommender models, the recommendations are computed according to rules that are deliberated based on the explicit specifications by the users. There are two types of knowledge-based recommenders such as the constraint-based recommender models and the case-based recommender [6].

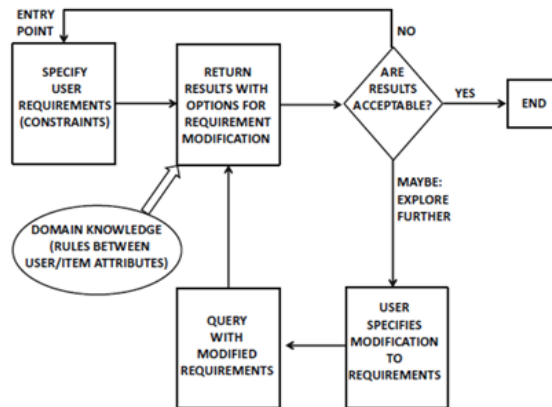


Fig. 7. Constraint-based recommender process [6]

The constraint-based recommender models are applied in a scenario where the user specifies the range of requirements, for example, the lower and higher limits as displayed in Fig. 7. The case-based recommender models are applied in a scenario where the user specifies attributes of the items and the model return results that are similar to the attributes that are specified as portrayed in Fig. 8.

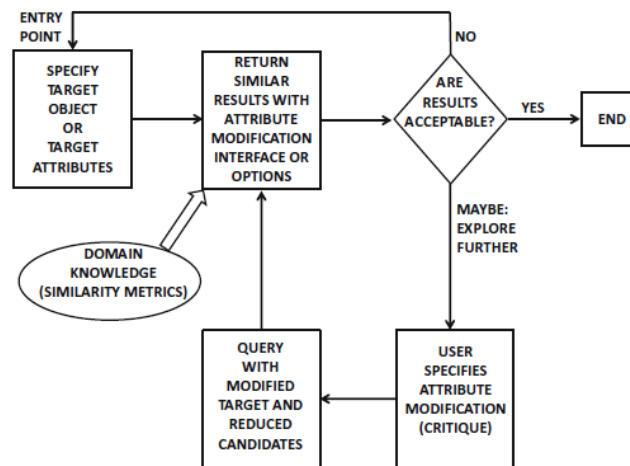


Fig. 8. Case-based recommender process [6]

2.2.4. Hybrid-based models

Hybrid recommender models can be designed in several ways. The first type is a parallel design by gaining weights from several recommender models as displayed in Fig. 9. The second type is a sequential design where the output of one recommender model is used to create the input features of another. Finally, the design may switch between different models depending on the scenarios, for example, a knowledge-based model during a cold start situation and a collaborative based model when enough rating are available [20].

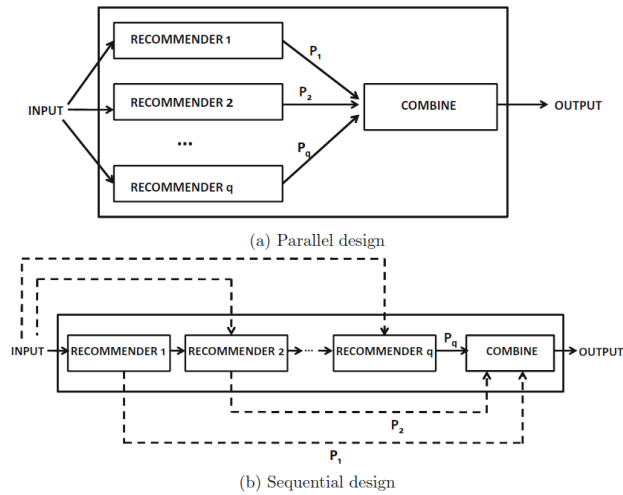


Fig. 9. Parallel or sequential hybrid recommender designs [6]

2.3. The application domains of recommender models

The reference [25] surveyed the application domains of recommendation models from 1996 to 2014, and as presented in Table 3, the highest number of recommender model applications is recorded in the e-resource domain which recommends content such as videos, music and documents to an individual.

Table 3. Domains of cases and implementations described in the publications [adapted from 25]

Domains \ Techniques	No. of listed references
E-government	9
E-business	5
E-commerce/E-shopping	8
E-library	6
E-learning	10
E-tourism	18
E-resource	27
E-group activity	21
Total	104

The next highest number of recommender model applications is recorded in the domain of e-group activity, which recommends items to a group of people or communities of like-minded people. E-tourism seems an upcoming domain due to the internet of things. Several domains which are late in adopting the recommender models are insurance, banking and healthcare probably due to its highly regulated environment, sterner expectations and concerns of personal data protection [26], [27].

3. Results and Discussion

The application of recommendation models in personalized marketing campaigns has been evolving since its introduction in the year 1990. One key area which created a breakthrough in the adoption of recommender models is the escalation in computing power which allows the use of machine learning algorithms to increase the accuracy of prediction and further personalize the recommendations to individual customers. However, it lacks a systematic classification of the appropriate use cases of different types of recommender models found in the literature. Therefore, choosing the right using machine learning algorithms remains a challenging task.

A conventional recommender model is developed based on a user's request for recommendations, known as a 'pull' model [28]. In recent years, recommendation models have been proactive where recommenders decide to 'push' its recommendations even when it is not openly requested [29], [30]. Therefore, the challenge is to decide when and how much to push so that it is not perceived by the user as annoying. A recommender model supposedly is required to capture both the users' short-term as well as long-term preferences. Short-term preferences are case-based, however, long-term preferences are developed by analyzing the user's historical transactions in the system and later compiled as a profile for that respective user. Both features are essential in predicting user behaviour at a certain point in time. Comprehensive research is required in developing hybrid models that are able to accurately predict the recommendations without leaning towards a user's short-term preferences that may be diverging from their long-term profile.

Different types of recommender models are applied in many domains depending on the requirements. The models are developed using one of the techniques such as content-based, collaborative-based, knowledge-based and hybrid-based where the more suitable and robust machine learning algorithms are used to make more fitting predictions to the customers. Recommender models also operate in mobile digital devices where many recommendations are made. Therefore, the recommender models design must consider the efficiency of performance with limited resources. Making more effective recommendations to satisfy the requirements of the customers is the key to stay active in this contemporary competitive business world. Depending on the scenario, objective and the application domain, choosing the right recommender model with efficient machine learning algorithm is crucial.

4. Conclusions

Recommender models created breakthroughs in personalized marketing campaigns. Whilst the e-commerce, e-resources and social media have been in the forefronts in applying recommendation models, insurance, banking and healthcare sectors have also huge opportunities to implement the personalized marketing concepts. Careful research is required in identifying the suitable machine learning algorithm to develop more effective recommender models. However, the sparsity of explicit product ratings continues to be a challenge for making a good recommendation. Hence, this can be remediated by combining it with the abundance of implicit feedback that is generated by the customers, for example from the various histories like purchases, shopping carts, searches, clicks, views, comments, or even shares. Further study is required in the deployment of the recommender system for mass applications with limited resources.

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