Chapter 1

INTRODUCTION

The increasing importance of the Web as a medium for electronic and business transactions has served as a driving force for the development of recommender systems technology. An important catalyst in this regard is the ease with which the Web enables users to provide feedback about their likes or dislikes. For example, consider a scenario of a content provider such as Netflix. In such cases, users are able to easily provide feedback with a simple click of a mouse. A typical methodology to provide feedback is in the form of ratings, in which users select numerical values from a specific evaluation system (e.g., five-star rating system) that specify their likes and dislikes of various items.[4]

Other forms of feedback are not quite as explicit but are even easier to collect in the Web-centric paradigm. For example, the simple act of a user buying or browsing an item may be viewed as an endorsement for that item. Such forms of feedback are commonly used by online merchants such as Amazon.com, and the collection of this type of data is completely effortless in terms of the work required of a customer. The basic idea of recommender systems is to utilize these various sources of data to infer customer interests. The entity to which the recommendation is provided is referred to as the user, and the product being recommended is also referred to as an item. Therefore, recommendation analysis is often based on the previous interaction between users and items, because past interests and proclivities are often good indicators of future choices. A notable exception is the case of knowledge-based recommender systems, in which the recommendations are suggested on the basis of user-specified requirements rather than the past history of the user.

So, what is the basic principle that underlies the working of recommendation algorithms? The basic principle of recommendations is that significant dependencies exist between user and item-centric activity. For example, a user who is interested in a historical documentary is more likely to be interested in another historical documentary or an educational program, rather than in an action movie. In many cases, various categories of items may show significant correlations, which can be leveraged to make more accurate recommendations. Alternatively, the dependencies may be present at the finer granularity of individual items rather than categories. These dependencies can be learned in a data-driven manner from the ratings matrix, and the resulting model is used to make predictions for target users. The larger the number of rated items that are available for a user, the easier it is to make robust predictions about the future behaviour of the user.

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Chapter 1 INTRODUCTION

Many different learning models can be used to accomplish this task. For example, the collective buying or rating behaviour of various users can be leveraged to create cohorts of similar users that are interested in similar products. The interests and actions of these cohorts can be leveraged to make recommendations to individual members of these cohorts.

The aforementioned description is based on a very simple family of recommendation algorithms, referred to as neighbourhood models. This family belongs to a broader class of models, referred to as collaborative filtering. The term “collaborative filtering” refers to the use of ratings from multiple users in a collaborative way to predict missing ratings. In practice, recommender systems can be more complex and data-rich, with a wide variety of auxiliary data types. For example, in content-based recommender systems, the content plays a primary role in the recommendation process, in which the ratings of users and the attribute descriptions of items are leveraged in order to make predictions. The basic idea is that user interests can be modelled on the basis of properties (or attributes) of the items they have rated or accessed in the past. A different framework is that of knowledge-based systems, in which users interactively specify their interests, and the user specification is combined with domain knowledge to provide recommendations. In advanced models, contextual data, such as temporal information, external knowledge, location information, social information, or network information, may be used[4].

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**Chapter 2**

**LITERATURE SURVEY**

Recommender systems (RS) which use data mining and information filtering techniques to provide products, services and information to potential customers have attracted a lot of attention of researchers. It has been regarded as an important tool to solve the information overload problem. While RS being originally a field dominated by computer scientists and is now a topic of interest also for mathematicians, physicists, and psychologists. [5]

The basic models for recommender systems work with two kinds of data, which are (i) the user-item interactions, such as ratings or buying behaviour, and (ii) the attribute information about the users and items such as textual profiles or relevant keywords. Methods that use the former are referred to as collaborative filtering methods, whereas methods that use the latter are referred to as content-based recommender methods. [6]

Recommended third generation systems are now at the very beginning of their development. The main innovation of such systems is their orientation to semantic models of representation and use of knowledge, in particular, knowledge about the user's personal profile. At present, the most natural and most developed way of formalizing semantic categories, which are usually used in decision-making processes, is ontology. For this reason, in modern and future systems, which are called third-generation recommender systems, ontology is viewed as a general framework for presenting diverse and diverse types of knowledge. Examples of such knowledge are, for example, knowledge of the user's personal profile, the context of decision making, the emotional state of the user when making a decision [7]

Two basic paradigms involved in generating recommendations for any recommender systems are collaborative Filtering and content-based filtering. Collaborative filtering [8] is a technique that uses information of a user like ratings or purchases made by the user to other users of the site who have a similar taste. This can be done either matching a similarity between users or items. The two approaches have been given the names User based collaborative filtering and Item based collaborative filtering. You tube and amazon recommends items based on item to item collaborative filtering. [9]

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Chapter 2 LITERATURE SURVEY

2.1 GroupLens Recommender System

GroupLens[4] was a pioneering recommender system, which was built as a research prototype for recommendation of Usenet news. The system collected ratings from Usenet readers and used them to predict whether or not other readers would like an article before they read it. Some of the earliest automated collaborative filtering algorithms were developed in the GroupLens1 setting. The general ideas developed by this group were also extended to other product settings such as books and movies. The corresponding recommender systems were referred to as BookLens and MovieLens, respectively. Aside from its pioneering contributions to collaborative filtering research, the GroupLens research team was notable for releasing several data sets during the early years of this field, when data sets were not easily available for benchmarking. Prominent examples include three data sets [688] from the MovieLens recommender system. These data sets are of successively increasing size, and they contain 105, 106, and 107 ratings, respectively.

2.2 Amazon.com Recommender System

Amazon.com [4] was also one of the pioneers in recommender systems, especially in the commercial setting. During the early years, it was one of the few retailers that had the foresight to realize the usefulness of this technology. Originally founded as a book e-retailer, the business expanded to virtually all forms of products. Consequently, Amazon.com now sells virtually all categories of products such as books, CDs, software, electronics, and so on. The recommendations in Amazon.com are provided on the basis of explicitly provided ratings, buying behaviour, and browsing behaviour. The ratings in Amazon.com are specified on a 5-point scale, with lowest rating being 1-star, and the highest rating being 5-star. The customer-specific buying and browsing data can be easily collected when users are logged in with an account authentication mechanism supported by Amazon. Recommendations are also provided to users on the main Web page of the site, whenever they log into their accounts. In many cases, explanations for recommendations are provided. For example, the relationship of a recommended item to previously purchased items may be included in the recommender system interface. The purchase or browsing behaviour of a user can be viewed as a type of implicit rating, as opposed to an explicit rating, which is specified by the user.

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Chapter 2 LITERATURE SURVEY

2.3 Netflix Movie Recommender System

Netflix was founded as a mail-order digital video disc (DVD) rental company [4] of movies and television shows, which was eventually expanded to streaming delivery. At the present time, the primary business of Netflix is that of providing streaming delivery of movies and television shows on a subscription basis. Netflix provides users the ability to rate the movies and television shows on a 5-point scale. Furthermore, the user actions in terms of watching various items are also stored by Netflix. These ratings and actions are then used by Netflix to make recommendations. Netflix does an excellent job of providing explanations for the recommended items. It explicitly provides examples of recommendations based on specific items that were watched by the user. Such information provides the user with additional information to decide whether or not to watch a specific movie. Presenting meaningful explanations is important to provide the user with an understanding of why they might find a particular movie interesting. This approach also makes it more likely for the user to act on the recommendation and truly improves the user experience. This type of interesting approach can also help improve customer loyalty and retention. Netflix has contributed significantly to the research community as a result of the Netflix Prize contest. This contest was designed to provide a forum for competition among various collaborative filtering algorithms contributed by contestants. A data set of Netflix movie ratings was released, and the task was to predict ratings of particular user-item combinations. For this purpose, Netflix provided both a training data set, and a qualifying data set. The training data set contained 100,480,507 ratings that 480,189 users gave to 17,770 movies. The training set included a smaller probe set containing 1,408,395 ratings. The probe set was based on more recent ratings than the remaining training data, and it was statistically similar to the portion of the data set with hidden ratings. This portion of the data set was referred to as the qualifying data set, and it contained over 2,817,131 triplets of the form User, Movie, GradeDate. Note that the triplet did not contain the actual rating, which was known only to the judges. Users needed to predict the ratings in the qualifying data set based on models of the training data. This prediction was scored by the judges (or an equivalent automated system), and the users were (continuously) informed of the prediction results on only half the qualifying data set on the leader-board.

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**Chapter 3**

**FUNDAMENTALS OF CONTENT-BASED RECOMMENDER SYSTEMS**

In content-based recommender systems, the descriptive attributes of items are used to make recommendations. The term “content” refers to these descriptions. In content-based methods, the ratings and buying behaviour of users are combined with the content information available in the items. For example, consider a situation where John has rated the movie Terminator highly, but we do not have access to the ratings of other users. Therefore, collaborative filtering methods are ruled out. However, the item description of Terminator contains similar genre keywords as other science fiction movies, such as Alien and Predator. In such cases, these movies can be recommended to John. In content-based methods, the item descriptions, which are labelled with ratings, are used as training data to create a user-specific classification or regression modelling problem. For each user, the training documents correspond to the descriptions of the items she has bought or rated. The class (or dependent) variable corresponds to the specified ratings or buying behaviour. These training documents are used to create a classification or regression model, which is specific to the user at hand (or active user). This user-specific model is used to predict whether the corresponding individual will like an item for which her rating or buying behaviour is unknown.[1]

In Content based approach, recommendation of objects is related to qualities or insight of objects rather than rankings of users[1] as shown in Figure 3.1.

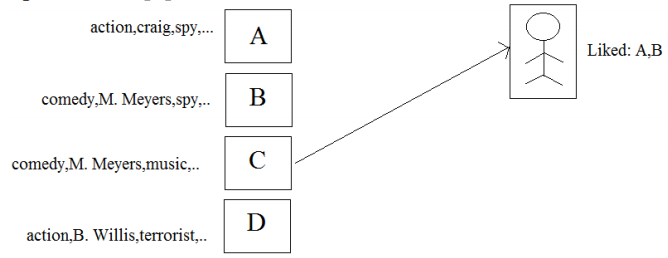


Figure 3.1 Content-based approach

. Content-based filtering method highlights more on the characteristics of items to produce recommendations. Content based approach is the best in predicting documents like

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web pages, publications, articles and news etc. In content based method, prediction is related to scholar profiles with attributes mined from the insight of the objects, the scholar has intended in the historical. Positively rated objects or items that got high rank are recommended to the user. Similarity is computed based on item attributes using appropriate distance measures. Content-based recommendation systems share in common describing the items that may be recommended, creating a profile of the user that describes the types of items the user likes, and comparing items to the user profile to determine what to recommend.

Systems realizing a content based recommendation method evaluate a collection of articles and attributes of objects ranked by a scholar in the past, and construct a design or profile of scholar interests using attributes of objects ranked by scholar. The user profile is a picture of user likeness in structured manner, implemented to predict novel relevant objects. The recommendation method fundamentally consists comparing the features of the scholar profile with the characteristics of a content element. Content-based recommendation systems (e.g. Last.fm6 and Amazon7) explore item features to find items which are similar to favorites of the user. Content based recommendation approach sift large repositories of objects (e.g. TV assets, articles, news, web pages, books, music tracks) with considering objects previously ranked by a scholar and constructing an analyse model of scholar favorites, stated as scholar profile, built upon the attributes of the objects ranked by the scholar. Then the scholar profile is analysed for recommending novel possibly relevant objects. Textual attributes are commonly used to describe objects and scholar profiles by CBRS. Therefore, this produces usual problems of uncertainty in natural language.

An expressive recommendation generated by CBF explores diverse kinds of models to identify match between articles. Vector Space Model like Term Frequency Inverse Document Frequency (TF/IDF) or Probabilistic models like Naive Bayes Classifier, Neural Networks or Decision Trees could be used to construct the relationship between different documents within a repository. To learn the basic model, statistical study or machine learning methods are used for making recommendation. Different scholar profiles does not affect recommendations generated by Content based method. CBF method has the potential to adjust its recommendations with changes in user profile within a short time.

Content-based recommendation systems recommend an item to a user based upon a description of the item and a profile of the user’s interests. While a user profile may be entered by the user, it is commonly learned from feedback the user provides on items. A variety of learning algorithms have been adapted to learning user profiles, and the choice of learning algorithm depends upon the representation of content.[1]

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**Chapter 4**

**HIGH LEVEL ARCHITECTURE OF CONTENT-BASED SYSTEMS**

Content-based Information Filtering (IF) systems need proper techniques for representing the items and producing the user profile, and some strategies for comparing the user profile with the item representation. The high level architecture of a content based recommender system[4] is depicted in Figure 4.1.

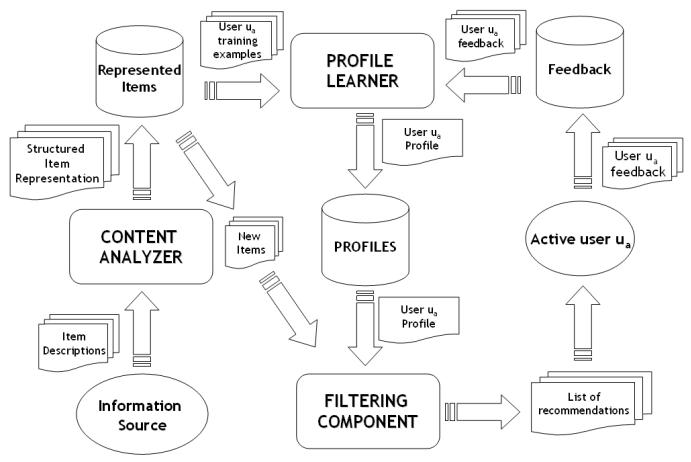


Figure 4.1 High level architecture of content-based recommender systems

The recommendation process is performed in three steps, each of which is handled by a separate component:

• **CONTENT ANALYSER** – When information has no structure (e.g. text), some kind of pre-processing step is needed to extract structured relevant information. The main responsibility of the component is to represent the content of items (e.g. documents, Web pages, news, product descriptions, etc.) coming from information sources in a form suitable for the next processing steps. Data items are analysed by feature extraction techniques in order to shift item representation from the original information space to the target one (e.g.

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Web pages represented as keyword vectors). This representation is the input to the

Profile learner and filtering component;

• **PROFILE LEARNER** – This module collects data representative of the user preferences and tries to generalize this data, in order to construct the user profile. Usually, the generalization strategy is realized through machine learning techniques, which are able to infer a model of user interests starting from items liked or disliked in the past. For instance, the PROFILE LEARNER of a Web page recommender can implement a relevance feedback method in which the learning technique combines vectors of positive and negative examples into a prototype vector representing the user profile. Training examples are Web pages on which a positive or negative feedback has been provided by the user;

• **FILTERING COMPONENT** – This module exploits the user profile to suggest relevant items by matching the profile representation against that of items to be recommended. The result is a binary or continuous relevance judgment (computed using some similarity metrics), the latter case resulting in a ranked list of potentially interesting items. In the above mentioned example, the matching is realized by computing the cosine similarity between the prototype vector and the item vectors.

The first step of the recommendation process is the one performed by the CONTENT ANALYSER, that usually borrows techniques from Information Retrieval systems. Item descriptions coming from Information Source are processed by the CONTENT ANALYSER, that extracts features (keywords, n-grams, concepts, . .) from unstructured text to produce a structured item representation, stored in the repository Represented Items.

In order to construct and update the profile of the active user ua (user for which recommendations must be provided) her reactions to items are collected in some way and recorded in the repository Feedback. These reactions, called annotations or feedback, together with the related item descriptions, are exploited during the process of learning a model useful to predict the actual relevance of newly presented items. Users can also explicitly define their areas of interest as an initial profile without providing any feedback.

Two different techniques can be adopted for recording user’s feedback. When a system requires the user to explicitly evaluate items, this technique is usually referred to as “explicit feedback”; the other technique, called “implicit feedback”, does not require any active user involvement, in the sense that feedback is derived from monitoring and analysing user’s activities.

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Explicit evaluations indicate how relevant or interesting an item is to the user. There are three main approaches to get explicit relevance feedback:

• Like/dislike – items are classified as “relevant” or “not relevant” by adopting a simple binary rating scale.

• Ratings – a discrete numeric scale is usually adopted to judge items. Alternatively, symbolic ratings are mapped to a numeric scale, where users have the possibility of rating a Web page as hot, lukewarm, or cold

• Text comments – Comments about a single item are collected and presented to the users as a means of facilitating the decision-making process. For instance, customer’s feedback at Amazon.com or eBay.com might help users in deciding whether an item has been appreciated by the community. Textual comments are helpful, but they can overload the active user because she must read and interpret each comment to decide if it is positive or negative, and to what degree. The literature proposes advanced techniques from the affective computing research area to make content-based recommenders able to automatically perform this kind of analysis.

Explicit feedback has the advantage of simplicity, albeit the adoption of numeric/symbolic scales increases the cognitive load on the user, and may not be adequate for catching user’s feeling about items. Implicit feedback methods are based on assigning a relevance score to specific user actions on an item, such as saving, discarding, printing, bookmarking, etc. The main advantage is that they do not require a direct user involvement, even though biasing is likely to occur, e.g. interruption of phone calls while reading.

In order to build the profile of the active user ua, the training set T Ra for ua must be defined. T Ra is a set of pairs ⟨Ik ,rk⟩, where rk is the rating provided by ua on the item representation Ik . Given a set of item representation labelled with ratings, the PROFILE LEARNER applies supervised learning algorithms to generate a predictive model – the user profile – which is usually stored in a profile repository for later use by the FILTERING COMPONENT. Given a new item representation, the FILTERING COMPONENT predicts whether it is likely to be of interest for the active user, by comparing features in the item representation to those in the representation of user preferences (stored in the user profile). Usually, the FILTERING COMPONENT implements some strategies to rank potentially interesting items according to the relevance with respect to the user profile. Top-ranked items

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are included in a list of recommendations La, that is presented to ua. User tastes usually change in time, therefore up-to-date information must be maintained and provided to the PROFILE LEARNER in order to automatically update the user profile. Further feedback is gathered on generated recommendations by letting users state their satisfaction or dissatisfaction with items in La. After gathering that feedback, the learning process is performed again on the new training set, and the resulting profile is adapted to the updated user interests. The iteration of the feedback-learning cycle over time allows the system to take into account the dynamic nature of user preferences.[2]

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**Chapter 5**

**CONCEPTS IN CONTENT-BASED RECOMMENDERS**

**5.1 Term Frequency (TF) and Inverse Document Frequency (IDF)**

TF is simply the frequency of a word in a document. IDF is the inverse of the document frequency among the whole corpus of documents. TF-IDF is used mainly because of two reasons: Suppose we search for “the rise of analytics” on Google**.**It is certain that “the” will occur more frequently than “analytics” but the relative importance of analytics is higher than the search query point of view. In such cases, TF-IDF weighting negates the effect of high frequency words in determining the importance of an item (document).[3]

But while calculating TF-IDF, log is used to dampen the effect of high frequency words. For example: TF = 3 vs TF = 4 is vastly different from TF = 10 vs TF = 1000. In other words the relevance of a word in a document cannot be measured as a simple raw count and hence the equation[3] as shown in Figure 5.1.

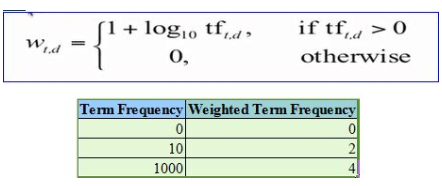
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Figure 5.1 TF\_IDF Equation

It can be seen that the effect of high frequency words is dampened and these values are more comparable to each other as opposed to the original raw term frequency.

After calculating TF-IDF scores, which items are closer to each other, rather closer to the user profile must be determined. This is accomplished using the **Vector Space Model** which computes the proximity based on the angle between the vectors.

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**5.2 Vector Space Model**

In this model, each item is stored as a vector of its attributes (which are also vectors) in an **n-dimensional space** and the angles between the vectors are calculated to **determine the similarity between the vectors**. Next, the user profile vectors are also created based on his actions on previous attributes of items and the similarity between an item and a user is also determined in a similar way[3] as shown in Figure 5.2.

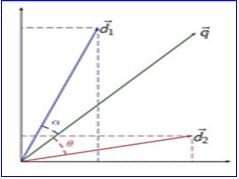


Figure 5.2 User profile vectors

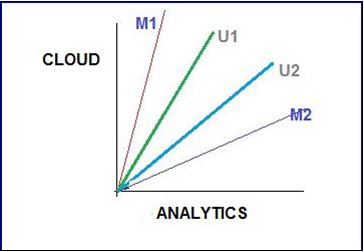


Figure 5.3 2-D representation of Cloud and Analytics

Shown above in Figure 5.3 is a 2-D representation of a two attributes[3], Cloud & Analytics. M1 & M2 are documents. U1 & U2 are users. The document M2 is more about Analytics than cloud whereas M1 is more about cloud than Analytics. I am sure you want to know how the relative importance of documents are measures.

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User U1, likes articles on the topic ‘cloud’ more than the ones on ‘analytics’ and vice-versa for user U2. The method of calculating the user’s likes / dislikes / measures is calculated by taking the cosine of the angle between the user profile vector **(Ui)**and the document vector.

The ultimate reason behind using cosine is that the **value of cosine will increase with decreasing value of the angle** between which signifies more similarity. The vectors are length normalized after which they become vectors of length 1 and then the cosine calculation is simply the sum-product of vectors.

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**Chapter 6**

**ADVANTAGES AND DRAWBACKS OF CONTENT-BASED FILTERING**

**6.1 Advantages**

The adoption of the content-based recommendation paradigm has several advantages when compared to the collaborative one[2]:

• **USER INDEPENDENCE** - Content-based recommenders exploit solely ratings provided by the active user to build her own profile. Instead, collaborative filtering methods need ratings from other users in order to find the “nearest neighbours” of the active user, i.e., users that have similar tastes since they rated the same items similarly. Then, only the items that are most liked by the neighbours of the active user will be recommended;

• **TRANSPARENCY** - Explanations on how the recommender system works can be provided by explicitly listing content features or descriptions that caused an item to occur in the list of recommendations. Those features are indicators to consult in order to decide whether to trust a recommendation. Conversely, collaborative systems are black boxes since the only explanation for an item recommendation is that unknown users with similar tastes liked that item;

• **NEW ITEM** - Content-based recommenders are capable of recommending items not yet rated by any user. As a consequence, they do not suffer from the first-rater problem, which affects collaborative recommenders which rely solely on users’ preferences to make recommendations. Therefore, until the new item is rated by a substantial number of users, the system would not be able to recommend it.

**6.2 Drawbacks**

Content-based systems have some limitations[2]:

• **LIMITED CONTENT ANALYSIS** - Content-based techniques have a natural limit in the number and type of features that are associated, whether automatically or manually, with the objects they recommend. Domain knowledge is often needed, e.g., for movie recommendations the system needs to know the actors and directors, and sometimes, domain

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Chapter 6 ADVANTAGES AND DRAWBACKS

ontologies are also needed. No content-based recommendation system can provide suitable suggestions if the analysed content does not contain enough information to discriminate items the user likes from items the user does not like. Some representations capture only certain aspects of the content, but there are many others that would influence a user’s experience. For instance, often there is not enough information in the word frequency to model the user interests in jokes or poems, while techniques for affective computing would be most appropriate. Again, for Web pages, feature extraction techniques from text completely ignore aesthetic qualities and additional multimedia information. To sum up, both automatic and manually assignment of features to items could not be sufficient to define distinguishing aspects of items that turn out to be necessary for the elicitation of user interests.

• **OVER-SPECIALIZATION** - Content-based recommenders have no inherent method for finding something unexpected. The system suggests items whose scores are high when matched against the user profile, hence the user is going to be recommended items similar to those already rated. This drawback is also called serendipity problem to highlight the tendency of the content-based systems to produce recommendations with a limited degree of novelty. To give an example, when a user has only rated movies directed by Stanley Kubrick, she will be recommended just that kind of movies. A “perfect” content-based technique would rarely find anything novel, limiting the range of applications for which it would be useful.

• **NEW USER** - Enough ratings have to be collected before a content-based recommender system can really understand user preferences and provide accurate recommendations. Therefore, when few ratings are available, as for a new user, the system will not be able to provide reliable recommendations.

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**Chapter 7**

**CONCLUSION**

Recommender systems require specialized methods to make them more effective in a wide variety of scenarios. A major problem in the effective use of such systems is the cold start problem, in which a sufficient number of ratings is not available at the beginning of the recommendation process. Therefore, specialized methods are often used to address this problem. In many cases, the context of the recommendation, such as the location, time, or social information, can significantly improve the recommendation process.[1]

Content-based recommendation systems recommend an item to a user based upon a description of the item and a profile of the user’s interests. While a user profile may be entered by the user, it is commonly learned from feedback the user provides on items. A variety of learning algorithms have been adapted to learning user profiles, and the choice of learning algorithm depends upon the representation of content.[2]

Content based filtering method is a domain-dependent and it highlights largely on the exploration of the features of items to produce predictions. Content based filtering approach is the utmost successful method in predicting documents such as news, web pages and publications. CBF method has the capability to change its recommendations with changes occurs in user profile within a very short period of time. CBF uses diverse types of prototypes to discover match between articles or documents for producing meaningful recommendations like keyword based model (Vector Space Model) for example, TF/IDF (Term Frequency Inverse Document Frequency).[4]

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**REFERENCES**

[1] Deepa Mandave, Govind S. Pole ″A Review on Content Based Recommendation System”, Vol. 4, Issue 11, November 2016.

[2] Pasquale Lops, Marco de Gemmis and Giovanni Semeraro “Content-based Recommender Systems: State of the Art and Trends”

[3] Michael J. Pazzani and Daniel Billsus “Content-Based Recommendation Systems”

[4] Recommender Systems, Aggarwal

[5] Achin Jain, Vanita Jain, Nidhi Kapoor ″A literature survey on recommendation system based on sentimental analysis″ Advanced Computational Intelligence, Vol.3, No.1, pp. 25-36, 2016.

[6] Assad Abbas, Limin Zhang, Samee U. Khan ″A survey on context-aware recommender systems based on computational intelligence techniques″, Computing, Vol.97, pp. 667–890, 2015

[7] Michael D. Ekstrand, John T. Riedl and Joseph A. Konstan, Collaborative Filtering Recommender Systems, Foundations and Trends in Human Computer Interaction, vol. 4, 2011, pp 81-173

[8] Sachin Walunj, Kishor Sadafale. An online Recommendation System for E-commerce Based On Apache Mahout Framework. SIGMIS-CPR. ACM 2013, pp 153-158.

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