An Improved Switching Hybrid Recommender System Using Naive Bayes Classifier and Collaborative Filtering

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Abstract— **Recommender Systems apply machine learning and data mining techniques for filtering unseen information and can predict whether a user would like a given resource. To date a number of recommendation algorithms have been proposed, where collaborative filtering and content-based filtering are the two most famous and adopted recommendation techniques. Collaborative filtering recommender systems recommend items by identifying other users with similar taste and use their opinions for recommendation; whereas content-based recommender systems recommend items based on the content information of the items. These systems suffer from scalability, data sparsity, over specialization, and cold-start problems resulting in poor quality recommendations and reduced coverage. Hybrid recommender systems combine individual systems to avoid certain aforementioned limitations of these systems. In this paper, we proposed a unique switching hybrid recommendation approach by combining a Naive Bayes classification approach with the collaborative filtering. Experimental results on two different data sets, show that the proposed algorithm is scalable and provide better performance–in terms of accuracy and coverage–than other algorithms while at the same time eliminates some recorded problems with the recommender systems.**

Keywords: Hybrid Recommender Systems; Collaborative Filtering; Content-Based Filtering; Naive Bayes Classifier.

1 Introduction

There has been an exponential increase in the volume of available digital information, electronic sources, and online services in recent years. This information overload has created a potential problem, which is how to filter and efficiently deliver relevant information to a user. Furthermore, information needs to be prioritized for a user rather than just filtering the right information, which can create information overload problems. Search engines help internet users by filtering pages to match explicit queries, but it is very difficult to specify what a user wants by using simple keywords. The Semantic Web, also provides some help to find useful information by allowing intelligent search queries, however it depends on the extent the web pages are annotated.

These problems highlight a need for information extraction systems that can filter unseen information and can predict whether a user would like a given source. Such systems are called *recommender systems*, and they mitigate the aforementioned problems to a great extent. Given a new item, recommender systems can predict with impressive accuracy whether a user would like this item or not, based on user preferences (likes- positive examples, and dislikes- negative examples), observed behaviour, and information (demographic or content information) about items [1, 2].

An example of the recommender system is the *Amazon*[1] recommender engine [3], which can filter through millions of available items based on the preferences or past browsing behaviour of a user and can make personal recommendations. Some other well-known examples are *Youtube*[2] video recommender service and *MovieLens*[3] movie recommender system, which recommend videos and movies based on the person's opinions. In these systems, a history of user's interactions with the system is stored which given rise to his preferences. The history of the user can be gathered by explicit feedback, where the user rates some items in some scale or by implicit feedback, the user's interaction with the item is observed- for instance, if a user purchases an item then this is a sign that he likes that item, his browsing behaviour, etc.

There are two main types of recommender systems: collaborative filtering and content-based filtering recommender systems. Collaborative filtering recommender systems [4, 5, 6, 7] recommend items by taking into account the taste (in terms of preferences of items) of users, under the assumption that users will be interested in items that users similar to them have rated highly. Examples of these systems include GroupLens system [8],

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[1]www.amazon.com
[2]www.youtube.com
[3]www.movielens.org

Ringo[4], etc. Collaborative filtering classified into two sub-categories: memory-based CF and model-based CF. Memory-based approaches [5] make a prediction by taking into account the entire collection of previous rated items by a user, examples include GroupLens recommender systems [8]. Model-based approaches [9] use rating patterns of users in the training set, group users into different classes, and use ratings of predefined classes to generate recommendation for an *active user*[5] on a *target item*[6], examples include item-based CF [10], Singular Value Decomposition (SVD) based models [11], bayesian networks [12], and clustering methods [13].

Content-based filtering recommender systems [14] recommend items based on the textual information of an item, under the assumption that users will like similar items to the ones they liked before. In these systems, an item of interest is defined by its associated features, for instance, NewsWeeder [15], a newsgroup filtering system uses the words of text as features. The textual description of items is used to build item profiles. User profiles can be constructed by building a model of the users preferences using the descriptions and types of the items that a user is interested in, or a history of users interactions with the system is stored (e.g. user purchase history, types of items he purchases together, his ratings, etc.). The history of the user can be gathered by explicit feedback or implicit feedback. Explicit feedback is noise free but the user is unlikely to rate many items, whereas, implicit feedback is noisy (error prone), but can collect a lot of training data [16]. In general, a trade-off between implicit and explicit user feedback is used. Creating and learning user profiles is a form of classification problem, where training data can be divided into two categories: items liked by a user, and item disliked by a user.

Recommendations can be presented to an active user in the followings two different ways: by predicting ratings of items a user has not seen before and by constructing a list of items ordered by his preferences. In the former case, an active user provides the prediction engine with the list of items to be predicted, prediction engine uses other users (or items) ratings or content information, and then predict how much the user would like the given item in some numeric or binary scale. In the latter case, different heuristics are used for producing an ordered list of items, sometimes termed as *top-N recommendations* [11, 17]. For example, in collaborative filtering recommender system this list is produced by making the rating predictions of all items an active user has not yet rated, sorting the list, and then keeping the top-N items the active user would like the most. In this paper, we focussed on the former case–predicting the ratings of items–however we can easily construct a list of top-N items for each user by selecting highly predicted items.

[4]www.ringo.com

[5]The user for whom the recommendations are computed.

[6]The item a system wants to recommend.

1.1 Problem Statement

The continuous increase of the users and items demands the following properties in a recommender system. First is the *scalability*, that is its ability to generate predictions quickly in user-item rating matrix consisting of millions of users and items. Second is to *find good items* and to ameliorate the *quality* of the recommendation for a customer. If a customer trusts and leverages a recommender system, and then discovers that he is unable to find what he wants then it is unlikely that he will continue with that system. Consequently, the most important task for a recommender system is to accurately predict the rating of the non-rated user/item combination and recommend items based on these predictions. These two properties are in conflict, since the less time an algorithm spends searching for neighbours, the more scalable it will be, but produces worse quality recommendations. Third its *coverage* should be maximum, i.e. it should be able to produce recommendation for all the existing items and users regardless of the *new item cold-start*[7] and *new user cold-start*[8] problems. Fourth, its performance should not degrade with *sparsity*. As the user-item rating matrix is very sparse, hence the system may be unable to make many product recommendation for a particular user.

Collaborative Filtering and Content-based filtering suffer from potential problems– such as over-specialization[9], sparsity, reduced coverage, scalability, and cold-start problems, which reduce the effectiveness of these systems. Hybrid recommender systems have been proposed to overcome some of the aforementioned problems. In this paper, we propose a *switching hybrid recommender system* [18] using naive Bayes and item-based CF. A switching hybrid system is intelligent in a sense that it can switch between recommendation techniques using some criterion. The benefit of switching hybrid is that it can make efficient use of strengths and weaknesses of its constitutional recommender systems. We show empirically that proposed recommender system outperform other recommender system algorithms in terms of MAE, ROC-Sensitivity, and coverage. We evaluate our algo-

[7]When a new item is added to the system, then it is not possible to get rating for that item from significant number of users, and consequently the CF recommender system would not be able to recommend that item. This problem is called new item *cold-start problem* [9].

[8]CF recommender system works by finding the similar users based on their ratings, however it is not possible to get ratings from a newly registered user. Therefore, the system cannot recommend any item to that user, a potential problem with recommender system called *new user cold-start problem* [9].

[9]Pure content-based filtering systems only recommend items that are the most similar to a users profile. In this way, a user cannot find any recommendation that is different from the ones it has already rated or seen.

rithm on MovieLens[10] and FilmTrust[11] datasets.

The rest of the paper has been organized as follows. Section 2 discusses the related work. Section 3 presents some background concepts relating to item-based CF, content-based filtering, and Naive Bayes classifier. Section 4 outlines the proposed algorithm. Section 5 describes the data set and metrics used in this work. Section 6 compares the performance of the proposed algorithm with the existing algorithms followed by conclusion in section 7.

2 Related Work

Pazzani [19] propose a hybrid recommendation approach in which a content-based profile of each user is used to find the similar users, which are used for making predictions. The author used Winnow to extract features from user's home page to build the user content-based profile. The problem with this approach is that if the content-based profile of a user is erroneous (may be due to synonyms problems or others), then it will results in poor recommendations. In [20], the authors proposed a hybrid recommender framework to recommend movies to users. In the content-based filtering part, they get extra information about movies from the IMDB[12] web site and view each movie as a text document. A Naive Bayes classifier is used for building user and item profiles, which can handle vectors of bags-of-words. The Naive Bayes classifier is used to approximate the missing entries in the user-item rating matrix, and a user-based CF is applied over this dense matrix. The problem with this approach is that it is not scalable. Our work combines Naive Bayes and Collaborative Filtering in a more scalable way than [20] and uses synonym detection and feature selection algorithms that produce accurate profiles of users resulting in improved predictions. The off-line cost of our approach and [20] is the same, i.e. the cost to build a naive Bayes classifier. However, our on-line cost (in the worse case) is less than or equal to [20][13]. A similar approach has been used in a book recommender system, LIBRA [21]. LIBRA downloads content information about book (meta data) from Amazon and extracts features using simple pattern-based information extraction system, and builds user models using a Naive Bayes classifier. A user can rate items using a numeric scale from 1 (lowest) to 10 (highest). It does not predict exact values, but rather presents items to a user according to his preferences. The authors in [22, 23] used demographic information about users and items for providing more accurate prediction for user-based and item-based CF. They proposed hybrid recommender system (lying between cascading and feature combination hybrid recommender systems [18]) in which demographic correlation between two items (or users) is applied over the candidate neighbours found after applying the rating correlation on the user-item rating matrix. This refined set of neighbours are used for generating predictions. However they completely miss the features of items for computing similarity. In [24], content-based filtering using the Rocchio's method is applied to maintain a term vector model that describe the user's area of interest. This model is then used by collaborative filtering to gather documents on basis of interest of community as a whole. Another example of hybrid systems is proposed in [25], where the author presented an on-line hybrid recommender system for news recommendation.

[10]www.grouplens.org/node/73
[11]www.filmtrust.com
[12]www.imdb.com
[13]See section 6.

3 Background

Let $M = \{ m_1, m_2, \cdots, m_x \}$ be the set of all users, $N = \{ n_1, n_2, \cdots, n_y \}$ be the set of all possible items that can be recommended, and r_{m_i,n_j} be the rating of user m_i on item n_j.

3.1 Item-Based Collaborative Filtering

Item-based CF [10] builds a model of item similarities using an off-line stage. Suppose we want to make prediction for an item n_t for an active user m_a. Let $M_{n_i n_j}$ be the set of all users, who have co-rated item n_i and n_j. There are three main steps in this approach as follows:

- In the first step, all items rated by an active user are retrieved.
- In the second step, target item's similarity is computed with the set of retrieved items. A set of K most similar items $n_1, n_2 \cdots n_K$ with their similarities $s_{n_1}, s_{n_2} \cdots s_{n_K}$ are selected. Similarity $sim(n_i, n_j)$, between two items n_i and n_j, is computed by first isolating the users who have rated these items (i.e. $M_{n_i n_j}$), and then applying the Adjusted Cosine similarity [10] as follows:

$$sim(n_i, n_j) = \frac{\sum\limits_{m \in M_{n_i,n_j}} \hat{r}_{m,n_i} \hat{r}_{m,n_j}}{\sqrt{\sum\limits_{m \in M_{n_i,n_j}} (\hat{r}_{m,n_i})^2 \sum\limits_{m \in M_{n_i,n_j}} (\hat{r}_{m,n_j})^2}}. \tag{1}$$

  Where, $\hat{r}_{m,n} = r_{m,n} - \overline{r}_m$, i.e. normalizing a rating by subtracting the respective user average from the rating, which is helpful in overcoming the discrepancies in user's rating scale. We multiplied similarity weights with a *Significance Weigthing factor* [26].
- In the last step, prediction for the target item is made by computing the weighted average of the active user's rating on the K most similar items. Using

weighted sum, the prediction p_{m_a,n_t} on item n_t for user m_a is computed as follows:

$$P_{m_a,n_t} = \frac{\sum_{i=1}^{K}(s_{n_t,i} \times r_{m_a,i})}{\sum_{i=1}^{K}(|s_{n_t,i}|)}. \tag{2}$$

3.2 Content-Based Filtering: Feature Extraction and Selection

Feature extraction techniques aim at finding the specific pieces of data in natural language documents [27], which are used for building both users and items profiles. These users and items profiles are then employed by a classifier for recommending resources. Documents, which typically are strings of characters, are transformed into a representation suitable for machine learning algorithms [28]. The documents are first converted into *tokens*, sequence of letters and digits, and then after *stop word*[14] removal, *stemming*[15] is performed . Each document is usually represented by a vector of n weighted index terms. A Vector Space Model [16] is the most commonly used document representation technique, in which documents are represented by vectors of words. Term Frequency-Inverse Document Frequency (TF-IDF) approach or others [28] can be used for determining the weight of a word in a document. TF-IDF approach is a well-known approach and uses the frequency of a word in a document as well as in the collection of documents for computing weights.

The feature space in a typical vector space model can be very large, which can be reduced by feature selection process. Feature selection process reduces the feature space by eliminating useless noise words having little (or no) discriminating power in a classifier, or having low signal-to-noise ratio. Several approaches are used for feature selection, such as DF-Thresholding, χ^2 statistic, and Information gain [28].

We downloaded information about movies from IMDB. After stop word removal and stemming, we constructed a vector of keywords, tags, directors, actors/actresses, and user reviews given to a movie in IMDB. We used TF-IDF approach for determining the weights of words in a document (i.e. movie) with DF-Thresholding feature selection. DF Thresholding approach computes the Document Frequency (DF) for each word in the training set and removes words having DF less than a predetermined threshold [29]. The assumption behind this is that, these rare words neither have the discriminating power for a category prediction nor do they influence the global performance.

[14]Stop words are frequently occurring words that carry no (or little) information.

[15]Stemming removes the case and inflections information from a word and maps it to the same stem. We used Porter Stemmer [16] algorithm for stemming.

3.3 Naive Bayes Classifier

The Naive Bayes classifier is based on the *Bayes theorem* with strong (Naive) independence assumption, and is suitable for the cases having high input dimensions. Using the Bayes theorem, the probability of a document d being in class C_j is calculated as follows:

$$P(C_j|d) = \frac{P(C_j)P(d|C_j)}{P(d)}, \tag{3}$$

where $P(C_j|d)$, $P(C_j)$, $P(d|C_j)$, and $P(d)$ are called the *posterior, prior, likelihood,* and *evidence* respectively.

The Naive assumption is that features are conditionality independent, for instance in a document the occurrence of words (features) do not depend upon each other[16] [29]. Formally, if a document has a set of features $F_1, \cdots, F_h$ then we can express equation 3 as follows:

$$P(C_j|d) = \frac{P(C_j)\prod_{i=1}^{h} P(F_i|C_j)}{P(F_1, \cdots, F_h)}. \tag{4}$$

An estimate $\widehat{P}(C_j)$ for $P(C_j)$ can be calculated as:

$$\widehat{P}(C_j) = \frac{A_j}{A}, \tag{5}$$

where A_j is the total number of training documents that belongs to category C_j and A is the total number of training documents. To classify a new document, Naive Bayes calculates posteriors for each class, and assigns the document to that particular class for which the posterior is the greatest.

In our case, we used the approach proposed in [21] for a book recommender system and in [30] for a movie recommender system, with the exception that we used *DF-Thresholding feature selection* scheme for selecting the most relevant features. We assume we have S possible classes, i.e. $C = \{C_1, C_2, \cdots, C_S\}$, where $S = 5$ for MovieLens and $S = 10$ for FilmTrust dataset. We have T types of information about a movie–keywords, tags, actors/actress, directors, plot, user comments, genre, and synopsis. We constructed a vector of bags-of-words [28], d_t against each type. The posteriror probability of a movie, n_y, is calculated as follows:

[16]Due to this assumption, the Naive Bayes classifier can handle high input dimension.

$$P(C_j|n_y) = \frac{P(C_j)\prod_{t=1}^{T}\prod_{i=1}^{|d_t|}P(w_{ti}|C_j,T_t)}{Pn_y}, \tag{6}$$

where, $P(w_{ti}|C_j,T_t)$ is the probability of a word w_{ti} given a class C_j and type T_t.

We use Laplace smoothing [29] to avoid the zero probabilities and log probabilities to avoid underflow.

4 Combining Item-Based CF and Naive Bayes Classifier for Improved Recommendations

We propose a framework for combining the item-based CF with the Naive Bayes classifier. The idea is to use Naive Bayes classifier in off-line stage for generating recommendations. The prediction computed by the item-based CF using on-line stage is used if we have less confidence in the prediction computed by the Naive Bayes, else Naive Bayes's prediction is used. We propose a simple approach for determining the confidence in the Naive Bayes's prediction.

Let $\hat{P}_{NB}$, $\hat{P}_{ICF}$, and $\hat{P}_{Final}$ represent the predictions generated by the Naive Bayes classifier, item-based CF, and the prediction we are confident to be accurate. Let $Pr(C_j)$ be the posterior probability of class j computed by the Naive Bayes classifier, L be a list containing the probabilities of each class, and $d(i,j)$ be the absolute difference between two class probabilities, i.e. $d(i,j) = |L(i) - L(j)| = |Pr(C_i) - Pr(C_j)|$ where $i \neq j$. The proposed hybrid approach is outlined in algorithm 1.

Step 2 to 5 ($\hat{P}_{ICF} = 0$) represent the case, where item-based CF fails to make a prediction[17]. In this case, we use prediction made by the Naive Bayes classifier. Step 7 to 16 determine the confidence in Naive Bayes's prediction. Confidence in Naive Bayes's prediction is high when the posterior probability of the predicted class is sufficiently larger than others. If $d(S, S-1)$ is sufficiently large, then we can assume that the actual value of an unknown rating has been predicted. The parameter α represents this difference and can be found empirically on training set. The parameter β tells us if the difference between the predictions made by the individual recommender systems is small, then again we are confident that Naive Bayes is able to predict a rating correctly. This is a kind of heuristic approach learnt from the prediction behaviour of CF and Naive Bayes. CF gives prediction in floating point scale, and Naive Bayes gives in integer point scale. CF recommender systems give accurate recommendation, but mostly they do not predict actual value, for example, if the actual value of an unknown rating is 4, then CF's prediction might be 3.9 (or 4.1, or some other value). On the other hand, Naive Bayes can give actual value, for example in the aforementioned case, it might give us 4. However, if Naive Bayes is not very confident, then it might result in prediction that is not close to the actual one, e.g. 3, 2, etc. We take the difference of individual recommender's predictions, and if it is less than a threshold (β), then we use Naive Bayes's prediction assuming that it has been predicted correctly. Steps 17 to 28 represent the case, where we have tie cases in Naive Bayes posterior probabilities. In this scenario, we take difference of each tie class with CF's prediction and use that class as final prediction, if the difference is less than β. Step 29 to 30 describe the case where we do not have enough trust in Naive Bayes's prediction, hence we use prediction made by the item-based CF.

[17]This can occur when no similar item is found against a target item, for example, in new-item cold start scenario–when only the active user has rated the target item.

Algorithm 1 Rec_{NBCF}

```
1:  procedure RECOMMEND($\hat{P}_{ICF}$, $\hat{P}_{NB}$, $L$)
2:      if ($\hat{P}_{ICF} == 0$) then
3:          a. $\hat{P}_{Final} \leftarrow \hat{P}_{NB}$
4:          b. return $\hat{P}_{Final}$
5:      end if
6:      Sort the list $L$ in ascending order, so that $L(1)$ contains the lowest value and $L(S)$ contains the highest value.
7:      if ($L(S) \neq L(S-1)$) then
8:          if $d(S, S-1) > \alpha$ then
9:              a. $\hat{P}_{Final} \leftarrow \hat{P}_{NB}$
10:             b. return $\hat{P}_{Final}$
11:         else
12:             if ($|\hat{P}_{NB} - \hat{P}_{ICF}| < \beta$) then
13:                 a. $\hat{P}_{Final} \leftarrow \hat{P}_{NB}$
14:                 b. return $\hat{P}_{Final}$
15:             end if
16:         end if
17:     else (i.e. $L(S) = L(S-1)$)
18:         for $t \leftarrow S-1, 1$ do
19:             if ($L(S) == L(t)$) then
20:                 if ($|\hat{P}_{ICF} - t| < \beta$) then
21:                     a. $\hat{P}_{Final} \leftarrow t$
22:                     b. return $\hat{P}_{Final}$
23:                 end if
24:             else
25:                 Break for
26:             end if
27:         end for
28:     end if
29:     $\hat{P}_{Final} \leftarrow \hat{P}_{ICF}$
30:     return $\hat{P}_{Final}$
31: end procedure
```

5 Experimental Evaluation

5.1 Dataset

We used MovieLens (ML) and FilmTrust (FT) datasets for evaluating our algorithm. MovieLens data set contains 943 users, 1682 movies, and 100 000 ratings on an integer scale 1 (bad) to 5 (excellent). MovieLens data set has been used in many research projects [10, 31, 23]. The sparsity of this dataset is 93.7% $\left(1 - \frac{non\ zero\ entries}{all\ possible\ entries} = 1 - \frac{100000}{943 \times 1682} = 0.937\right)$.

we created the second dataset by crawling the FilmTrust website. The dataset retrieved (on 10th of March 2009) contains 1592 users, 1930 movies, and 28 645 ratings on a floating point scale of 1 (bad) to 10 (excellent). The sparsity of this dataset is 99.06%[18].

5.2 Metrics

Several metrics have been used for evaluating recommender systems which can broadly be categorized into *Predictive Accuracy Metrics*, *Classification Accuracy Metrics*, and *Rank Accuracy Metrics* [32]. The Predictive Accuracy Metrics measure how close is the recommender system's predicted value of a rating, with the true value of that rating assigned by the user. These metrics include mean absolute error, mean square error, and normalized mean absolute error, and have been used in research projects such as [12, 33, 11, 10]. The Classification Accuracy Metrics determine the frequency of decisions made by a recommender system, for finding and recommending a good item to a user. These metrics include precision, recall, $F1$ measure, and Receiver Operating Characteristic curve, and have been used in [11, 34]. The last category of metrics, Rank Accuracy Metrics measure the proximity between the ordering predicted by a recommender system to the ordering given by the actual user, for the same set of items. These metrics include half-life utility metric proposed by Brease [12].

Our specific task in this paper is to predict scores for items that already have been rated by actual users, and to check how well this prediction helps users in selecting high quality items. Keeping this into account, we use *Mean Absolute Error (MAE)* and *Receiver Operating Characteristic (ROC) sensitivity*.

MAE measures the average absolute deviation between a recommender system's predicted rating and a true rating assigned by the user[19]. It is computed as follows:

$$MAE = \frac{\sum_{i=1}^{N} |r_{p_i} - r_{a_i}|}{N},$$

where r_{p_i} and r_{a_i} are the predicted and actual values of a rating respectively, and N is the total number of items that have been rated. It has been used in [12, 10].

ROC is the extent to which an information filtering system can distinguish between good and bad items. *ROC sensitivity* measures the probability with which a system accept a good item. The ROC sensitivity ranges from 1 (perfect) to 0 (imperfect) with 0.5 for random. To use this metric for recommender systems, we must first determine which items are good (*signal*) and which are bad (*noise*). In [35, 30] the authors consider a movie "good" if the user rated it with a rating of 4 or higher and "bad " otherwise. The flaw with this approach is that it does not take into account the inherent difference in the user rating scale–a user may consider a rating of 3 in a 5 point scale to be good, while another may consider it bad. We consider an item good if a user rated it with a score higher than his average (in the training set) and bad otherwise.

Furthermore, we used *coverage* that measures how many items a recommender system can make recommendation for. It has been used in [32]. We did not take coverage as the percentage of items that can be recommended/predicted from all available ones. The reason is, a recommendation algorithm can increase coverage by making bogus predictions, hence coverage and accuracy must be measured simultaneously. We selected only those items that have already been rated by the actual users.

6 Result and Discussion

We randomly selected 20% ratings of each user as the test set and used the remaining 80% as training set. We further subdivided our training set into a test set and training set for measuring the parameters sensitivity. For learning the parameters, we conducted 5-fold cross validation on the 80% training set, by randomly selecting the different test and training set each time, and taking the average of results.

We compared our algorithm with six different algorithms: user-based CF using Pearson correlation with default voting ($UBCF_{DV}$) [12], item-based CF (IBCF) using adjusted-cosine similarity[20] [10], a hybrid recommendation algorithm, IDemo4, proposed in [23], a Naive Bayes classification approach (NB) using item features information, a naive hybrid approach (NH) for generating recommendation[21], and the content-boosted algorithm (CB) proposed in [20]. Furthermore, we tuned all algorithms for the best mentioning parameters.

[18]Both dataset can be downloaded from: https://sourceforge.net/projects/hybridrecommend.

[19]The goal of a recommendation algorithm is to minimize MAE.

[20]With the exception that for FilmTrust dataset, we add 1 to all similarities, i.e. $sim(i, j) = sim(i, j) + 1$. The reason is that, it is very sparse and most of the similarities were negative resulting in poor performance.

[21]We take average of the prediction generated by a Naive Bayes and an item-based CF.

Table 1: A comparison of proposed algorithm with existing in terms of cost (based on [31]), accuracy metrics, and coverage

Algorithm	On-line Cost	Best MAE		ROC-Sensitivity		Coverage	
		(ML)	(FT)	(ML)	(FT)	(ML)	(FT)
$UBCF_{DV}$	$O(M^2N) + O(NM)$	0.766	1.441	0.706	0.563	99.424	93.611
IBCF	$O(N^2)$	0.763	1.421	0.733	0.605	99.221	92.312
IDemo4	$O(N^2)$	0.749	1.407	0.739	0.621	99.541	94.435
Rec_{NBCF}	$O(N^2) + O(Mf)$	**0.696**	**1.341**	**0.778**	**0.657**	**100**	**99.992**
NB	$O(Mf)$	0.808	1.462	0.703	0.571	100	99.992
NH	$O(N^2) + O(Mf)$	0.785	1.438	0.712	0.586	100	99.992
CB	$O(M^2N) + O(NM) + O(Mf)$	0.721	1.378	0.741	0.611	100	**99.995**

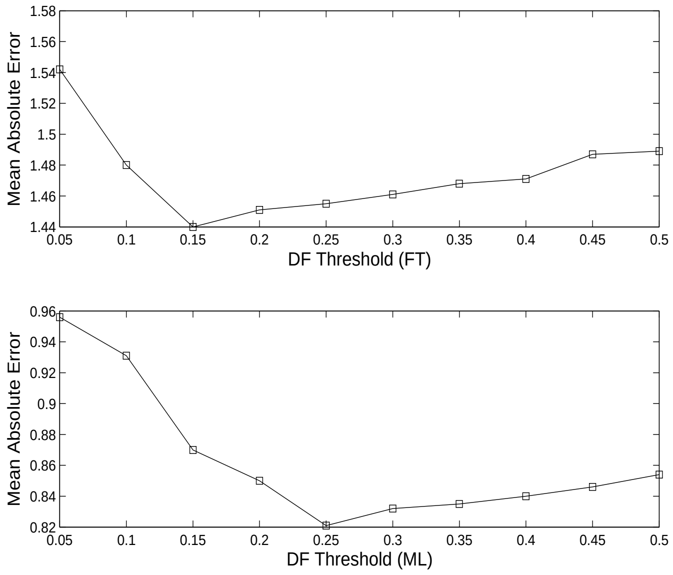


Figure 1: Determining the optimal value of DF.

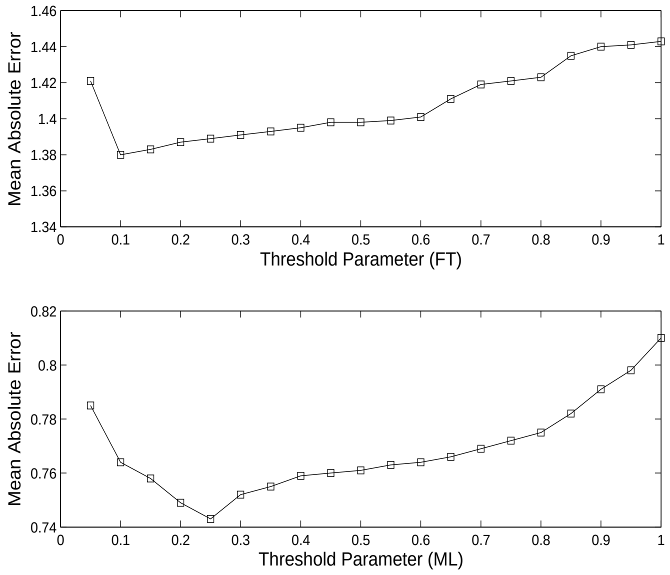


Figure 2: Determining the optimal value of α.

6.1 Learning Optimal Values of Parameters

The purpose of these experiments is to determine, which of the parameters affect the prediction quality of the proposed algorithm, and to determine their optimal values.

6.1.1 Optimal Value of DF Threshold Parameter

For determining the optimal value of DF, we varied the value of DF from 0 to 0.5 with a difference of 0.05[22]. The results are shown in figure 1. Figure 1 shows that $DF = 0.25$ and $DF = 0.15$ gave the lowest MAE for MovieLens and FilmTrust dataset. It is worth noting that, the values of parameters are found to be different for MovieLens and FilmTrust dataset, which is due to the fact that both dataset have different density, rating distribution, and rating scale.

[22]$DF = 0.05$ means that the word should occur at-least in 5% of the movies seen by an active user, to be considered as a valid feature.

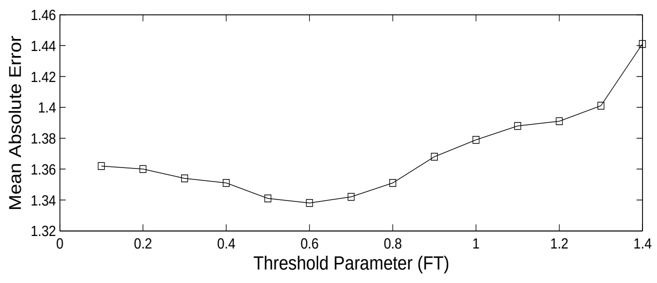
6.1.2 Optimal Value of α

For determining the optimal value of α, we kept $\beta = 10$, and varied the value of α from 0 to 1.0 with a difference of 0.05[23]. The results are shown in figure 2. Figure 2 shows that $\alpha = 0.25$ and $\alpha = 0.1$ gave the lowest MAE for MovieLens and FilmTrust dataset. We note that the values of parameters are found different for MovieLens and FilmTrust dataset.

6.1.3 Optimal Value of β

For determining the optimal value of β, wee kept $\alpha = 0.25$ and $\alpha = 0.1$ for MovieLens and FilmTrust dataset, and varied the value of β from 0 to 1.4 with a difference of 0.1. The results are shown in figure 2. Figure 2 shows that $\alpha = 0.4$ and $\alpha = 0.6$ gave the lowest MAE for MovieLens and FilmTrust dataset respectively.

[23]This value is chosen, so that parameter β does not have any effect on the selection of optimal value of α.



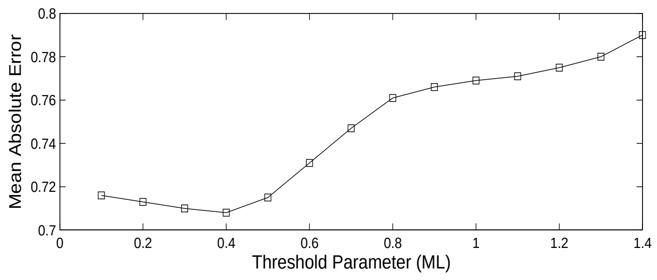


Figure 3: Determining the optimal value of β.

6.2 Performance Evaluation With Other Algorithms

6.2.1 Performance Evaluation in Terms of MAE, ROC-Sensitivity, and Coverage

Table 1 shows the on-line cost[24] of algorithms with their respective MAE, ROC-sensitivity, and coverage. We show the best results and the results of proposed algorithm in bold. Here, f is the number of features/words in the dictionary (used in Naive Bayes classifier). It is worth noting that for FilmTrust dataset, ROC sensitivity is lower, for all algorithms in general, as compared to the MovieLens dataset. We believe that it is due to the rating distribution. Furthermore, the coverage of the algorithms is much lower in the case of FilmTrust dataset, which is due to the reason that it is very sparse (99%). The table depicts that the proposed algorithm is scalable and practical as its on-line cost is less or equal to the cost of other algorithms.

Table 1 shows that the proposed algorithm outperforms other significantly in terms of MAE, ROC-sensitivity, and coverage. It is because, when Naive Bayes classifier has sufficiently large confidence in prediction, then it can correctly classify an instance (a unknown rating). In our case, Naive Bayes classifier was able to accurately predict about 40% and 36% ratings of the test set in the case of MovieLens and FilmTrust dataset respectively, resulting in the reduced MAE, increased ROC-sensivity and coverage.

[24]It is the cost for generating predictions for N items. We assume we compute item similarities and train Naive Bayes classifier in off-line fashion.

Table 2: Performance evaluation in new item cold-start problem

Algo.	**MAE**0		**MAE**2		**MAE**5	
	(ML)	**(FT)**	**(ML)**	**(FT)**	**(ML)**	**(FT)**
$UBCF_{DV}$	–	–	1.235	2.223	0.932	1.825
IBCF	–	–	1.209	2.172	0.873	1.764
IDemo4	–	–	1.191	2.162	0.852	1.682
CB	0.831	1.481	0.821	1.456	0.811	**1.448**
Rec_{NBCF}	**0.822**	**1.459**	**0.818**	**1.452**	**0.809**	**1.451**

6.2.2 Performance Evaluation Under Cold-Start Scenarios

We checked the performance of the algorithm under new item cold-start problems[25]. When an item is rated by only few users, then item-based and user-based CF will not give us good results. Our proposed scheme works well in new item cold-start problem scenario, as it does not solely depend on the number of users who have rated the target item for finding the similarity. For testing our algorithm in this scenario, we selected 1000 random samples of user/item pairs from the test set. While making prediction for a target item, the number of users in the training set who have rated target item were kept 0, 2, and 5. The corresponding MAE; represented by $MAE0$, $MAE2$, $MAE5$, is shown in table 2.

Table 2 shows that CF and IDemo4 fail to make prediction when only the active user rated the target item, and in general they gave inaccurate predictions. It is worth noting that, in e-commerce domains (e.g. Amazon), there may be millions of items that are rated by only a few users (< 5). In this scenario, CF and related approaches would results in inaccurate recommendations. The poor performance of user-based CF is due to the reason that, we have less neighbours against an active user, hence performance degrades. The reason in case of item-based CF is that, the similar items found after applying rating correlation may be not actually similar. As while finding similarity, we isolate all users who have rated both target item and the item we find similarity with. In this case, we have maximum 5 users who have rated both items, as a result, similarity found by adjusted cosine measure will be misleading. The IDemo4 produces poor results, as it operates over candidate neighbouring items found after applying the rating similarity. Both content-boosted and Rec_{NBCF} make effective use of user's content profile that can be used by a classifier for making predictions.

[25]It must be noted that our algorithm will not give good results in the case of new user cold-start problems. The reason is that we do not have enough training data to train the Naive Bayes classifier. This problem can be effectively solved by applying the vector similarity [12] over user or item's content profiles to find similar users or items, which can be used for making predictions.

6.2.3 Performance Evaluation In Terms of Cost

The cost of the proposed algorithm is given in table 1. We are using item-based CF, whose on-line cost is less than that of user-based CF used in [20][26]. Even if we consider using naive Bayes classifier to fill the user-item rating matrix and then use item-based CF over this filled matrix, then our cost will be less than that. The reason is in the filled matrix case, one has to go through all the filled rows of matrix for finding the similar items. For a large e-commerce system like Amazon, where we already have millions of neighbours against an active user/item, filling the matrix and then going through all the users/items for finding the similar users/items in not pragmatic due to limited memory and other constraint on the execution time of the recommender system.

7 Conclusion And Future Work

In this paper, we have proposed a switching hybrid recommendation approach by combining item-based collaborative filtering with a Naive Bayes classifier. We empirically show that our recommendation approach outperform others in terms of accuracy, and coverage and is more scalable. As a future work, we would like to apply Support Vector Machines over features vectors for generating recommendations. Furthermore, we would like to evaluate our algorithms on dataset of domains other than movies, such as BookCrossing[27] dataset.

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