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A SURVEY ON RECOMMENDER SYSTEM TECHNIQUES AND THEIR APPLICATIONS

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ABSTRACT

Recommender systems are web-based systems which help in the reduction or eradication of information overload in an information system. Recommender systems study the characteristics of a system user by identifying their ratings, purchases or other demographic attributes and then use the information gathered on the user to subsequently provide recommendation of items to the user. The design of the recommender system has to do with the use of various techniques such as the collaborative filtering technique, the content-based technique, and the hybrid technique. The collaborative filtering technique involves knowing the similarity between users and how they correlate with each other as a result of their activities on the platform. The content based filtering involves the identification of the contents and attributes of various items provided to the users while the hybrid technique involves the combination of both the collaborative and content based filtering techniques. The application of any of these techniques depends on the dataset available, area of application and also the performance expected of the design. This paper provides an extensive study on these techniques, stating their applications, their advantages and disadvantages. The outcome presented researchers with choices while implementing recommender systems.

INTRODUCTION

The advancement in technology has brought about the growth and improvement in information systems (Katarya *et al.*, 2016). This has led to the design of improved information retrieval systems which provide users with the needed advantage in information retrieval and eradicating the concept of information overload. According to Al-Badarenah *et al.* (2016), recommender systems are applications that are designed to help reduce the stress users go through to access information on information management systems and also the provision of recommendations to various users with respect to their choices and preferences. It was first brought to limelight in the 1990's with the invention of Tapestry (Melville *et al.*, 2017a). The goal of a recommender system is to generate meaningful item suggestions for users on items or products that might interest them presently or in the future as a result of the previous product choices or preferences on such products (Melville *et al.*, 2017b).

There are various techniques employed in the design of a recommender system and they include: the collaborative filtering technique (memory based and model based), which focuses on the user to user similarity or item to item similarity (Ekstrand *et al.*, 2011). The content base technique which is concerned with analysing the content of the user or item profiles (Ghauth *et al.*, 2010) and the hybrid technique which combines the collaborative filtering technique and content based techniques by eradicating the limitations of each approach to produce better recommendations. Choosing any of these techniques for recommender system design solely depends on the dataset available and also the expected output. We shall discuss in details, the various recommender system techniques in the part two of this paper.

METHODOLOGY

Our work focuses on the popular recommender system techniques, stating how they can be applied plus their advantages and disadvantages. More emphasis is laid on the calculations involved in collaborative filtering technique with an illustration. From the work which was done by Ogbozor *et al.* (2020) on collaborative filtering optimization, we extracted the rating matrix for 4 users on 6 items as seen in table 1. The rating values represents our dataset, which we used to illustrate how the Pearson correlation coefficient can be applied when using the collaborative filtering technique. Using the matrix of **user x ratings** which contains our values, we worked out the similarity value between the users and also the items (using equation 2.1 and 2.2), as seen in table 3 and 5. We further showcased how prediction of items to a user is done while using the technique. The illustration and the results provides more insight on Pearson correlation coefficient's application on collaborative filtering technique, and will help researchers during computation process in their design.

Recommender System Techniques

Techniques used in the design of recommender system is mainly classified into three: Collaborative filtering technique, Content-based filtering technique and the Hybrid technique. Each of these techniques have its own mode of application on recommender systems.

As earlier stated, the application of any of this technique significantly depend on the area of application, dataset available and the expected outcome. For example, the collaborative filtering techniques is mostly applied on an e-commerce/e-learning platform where user to user recommendation will work perfectly. The content-based filtering technique is mostly applied on news platforms where recommendations are based on the content of an article. While the hybrid technique can suit any platform because of their dynamic nature.

Collaborative filtering technique

Just like the name "collaborative" suggests, it is all about finding the correlation, relationship or similarity between users or between items. Collaborative filtering technique makes automatic prediction to an active user resulting from his similarity in preference and interest with an already existing user (Chen *et al.*, 2018). This approach focuses on relationship between two users and how items can be recommended to one based on his similarity with the other one.

Collaborative filtering technique comes in two forms namely: the memory based collaborative filtering and the model based collaborative filtering.

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a. Memory-Based Collaborative Filtering (Neighbourhood)

The memory-based collaborative filtering method is subdivided into user-based method and item-based method. The user-based method tends to find the similarity between various users in the system by forming the neighbourhood of all the other existing users who have the same preferences for items via ratings, user demographics, links clicked or any behavioural learning process which the system is designed to work with (Okon *et al.*, 2018). The neighbourhood formation is the first stage which is done while using both user-based and item-based method. This is achieved by using some similarity measures like the cosine measure and Pearson correlation coefficients (Chen *et al.*, 2018), with the latter being the most used similarity measure in this literature (Melville *et al.*, 2017a). The next stage is the prediction $P_{(a,i)}$ of the best item for the active user as seen in equation 2.1 (Chen *et al.*, 2018), so as to recommend the same item which had been rated by the existing user(s) to the target user. Equation 2.1, is used to achieve this.

$$P_{(a,i)} = \overline{r_a} + \frac{\sum_{u\in K}(r_{u,i}-\bar{r}_u) \times r_{(a,u)}}{\sum_{u\in K} r_{(a,u)}} \qquad (1)$$

where $\overline{r_a}$ is the mean rating of the active user on items, $r_{u,i}$ is the existing user's rating on item *i*. $\bar{r}_u$ is the existing user's mean rating for various items and **k** represents the neighbours of the active user which **u** must be a part of and $r_{(a,u)}$ is the similarity value between the user and the best neighbour. The Pearson correlation coefficients (equation 2.2) is the measure of the degree of closeness or relationship which exists between two variables found in the same operational space. The Pearson correlation coefficient is important when calculating the similarity or difference between users during the neighbourhood formation while designing a recommender system. The result of this is always within the range of -1 through 1, with -1 indicating a negative relationship between users meaning that users rated same item differently (Chen *et al.*, 2018). The value 1, represents the positive relationship which indicates that the users rated items very likely.

$$r_{(a,u)} = \frac{\sum_i (r_{a,i}-\overline{r_a})(r_{u,i}-\overline{r_u})}{\sum_i \sqrt{(r_{a,i}-\bar{r}_a)^2}\sqrt{(r_{u,i}-\overline{r_u})^2}} \qquad (2)$$

Equation 2.2 is used to compute the degree of correlation between our target user $\boldsymbol{a}$ and an existing user $\boldsymbol{u}$. The rating for user $\boldsymbol{u}$ for an item $\boldsymbol{i}$ is shown as $\boldsymbol{r_{u,i}}$ and in a similar way, the rating of a target user $\boldsymbol{a}$ for an item $\boldsymbol{i}$ is shown as $\boldsymbol{r_{a,i}}$. The mean rating of a given existing user and that of a target user is represented as $\bar{r}_u$ and $\bar{r}_a$, respectively.

Table 1, contains datasets from a platform developed by Ogbozor *et al.* (2020), which shows how some selected users have rated items. The platform is an e-commerce site which comprises of 2000 users, 15000 products and 5000 ratings on the products. The users log on to purchase and rate the available products. We have selected 4 users and the rating they have given to 6 items, for the purpose of this survey. User $\mathbf{U_a}$ represents our active user while users $\mathbf{U_1}$, $\mathbf{U_2}$, and $\mathbf{U_3}$ are our existing users.

An illustration of how the collaborative filtering technique uses the Pearson correlation metric in equation 2.2, to find the similarities between users, as well as predicting the active user's rating for an item using equation 2.1 is shown below using the user's item ratings table.

Table 1: A fragment of user-item rating matrix for a fashion recommender system

	I_1	I_2	I_3	I_4	I_5	I_6
U_a	3	4		3	5	
U_1	4	5		4	3	
U_2	1	3	4		3	
U_3	2		4			

User **a** represents our active user ratings and users U_1, U_2, U_3 represents the rating of existing users for the items. Below is the similarity computation for the active user **a** and user U_1. Table 2 shows the computation of the active user a and user U_1 relationship.

Table 2: Similarity computation for the active user **a** and an existing user U_1

Items S/N	r_a	r_u	$(r_a - \overline{r_a})$	$(r_u - \overline{r_u})$	$(r_a - \overline{r_a})(r_u - \overline{r_u})$	$(r_a - \bar{r}a)^2$	$(r_u - \overline{r_u})^2$
1	3	4	1	1.4	1.4	1	1.96
2	4	5	2	2.4	4.8	4	5.76
3	0	0	-2	-2.6	5.2	4	6.76
4	0	4	-2	1.4	-2.8	4	1.96
5	5	3	3	0.4	1.2	9	0.16
6	0	0	-2	-2.6	5.2	4	6.76
	$\overline{r_a}$ = 12/6 = 2	$\overline{r_u}$ =16/6 =2.6			$\sum$=15	$\sum$ =26	$\sum$=23.36

From the above values in table 2, the relationship between the active user **a** and the existing user U_1 will be:

$$r_{(a,u)} = \frac{\sum_i (r_{a,i} - \overline{r_a})(r_{u,i} - \overline{r_u})}{\sum_i \sqrt{(r_{a,i} - \bar{r}a)^2} \sqrt{(r_{u,i} - \overline{r_u})^2}} = \frac{15}{\sqrt{26 * 23.36}} = 0.6$$

The above calculations were done to get the similarity values between the active user **a** and users U_2, U_3 and their values are shown in table 3. From table 3, user U_1 have the highest similarity value with the active user **a** (the coloured row from table 1) followed by user U_2 and U_3 respectively as seen in table 3. This implies that users U_1 and U_2 will represent the neighbours (K) of the active user **a**, with user U_1 seen as the best neighbour (n) whose items will be recommended to user **a**.

Table 3: User similarity value table

Users	Similarity ratio with user a
U_1	0.60
U_2	0.16
U_3	0.03

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Using equation 2.1, we can then predict the rating of the active user **a** for item $\mathbf{I_4}$ in table 1.

Solution

To predict the rating of the active user **a** for item $\mathbf{I_4}$, we find the summation of the differences between the mean ratings and the normal ratings which the existing users **u** have giving to item I, multiply it by their corresponding similarity values with the active user **a** and add the value to the mean rating $\overline{r_a}$ of the active user **a**.

Note: **u** must be neighbours of the active user **a**.

$$P_{(a,i)} = \overline{r_a} + \frac{\sum_{u \in K}(r_{u,i} - \bar{r}_u) \times r_{(a,u)}}{\sum_{u \in K} r_{(a,u)}} = \frac{0.4 * 0.60}{0.60 + 0.16 + 0.03} = 2 + \frac{0.4 * 0.60}{0.79} = 2.3$$

(active user's rating for item 4)

The item-based neighbourhood method unlike the user-based method, computes similarity between user-rated items. Similarity calculation here is done on the columns of the rating matrix table by applying the adjusted cosine model. (Melville *et al.*, 2017a) proposed an item-based neighbourhood method because of the complexity involved in user-user similarity computation which is used in the user-based technique. Instead of doing the similarity computation on the rows of the rating table just like in the case of user based collaborative filtering technique, the item based technique uses the columns for its computation as it focuses on the items as seen in equation 2.3 which is also the Pearson correlation metric (Melville *et al.*, 2017a).

$$\mathbf{r}_{(i,j)} = \frac{\sum_u (r_{u,i} - \bar{r}_i)(r_{u,j} - \bar{r}_j)}{\sum_u \sqrt{(r_{u,i} - \bar{r}_i)^2} \sqrt{(r_{u,j} - \bar{r}_j)^2}} \quad (3)$$

in equation 2.3, $r_{u,i}$ represents the rating of a user u on item i, $r_{u,j}$ is the rating value of the user u for item j, $\bar{r}_i$ and $\bar{r}_j$ are the mean ratings for items i and j respectively. The value gotten after the computation of the similarity between items are also within the ranges of -1 to 1 as we have for user-based neighbourhood method. Equation 2.4 (Chen *et al.*, 2018), is used to predict what rating a user will give to an item.

$$\mathbf{P}_{(a,i)} = \frac{\sum_{j \in K} r_{a,j} . r_{i,j}}{\sum_{j \in K} |r_{i,j}|} \quad (4)$$

k is the neighbourhood of items which item **j** is part of, $r_{i,j}$ is the item similarity value and $r_{a,j}$ is user **a**'s rating for item j.

A simple illustration on how similarity values can be gotten while using the item based collaborative filtering recommender system is shown below using table 4. Using the data contained in table 1.

Note: From table 1, the first column is the target item while the other columns are the already existing items. Table 4a shows the computation of the similarity between item i and j_1.

Table 4. Similarity computation between item **I₁** and item **I₂**

Items S/N	r_i	r_j	$(r_u - \bar{r_i})$	$(r_u - \bar{r_j})$	$(r_u - \overline{r_u})$ $(r_u - \bar{r_j})$	$(r_u - \overline{ri})^2$	$(r_u - \bar{r_j})^2$
1	**3**	**4**	**0.5**	**1**	**0.5**	**0.25**	**1**
2	**4**	**5**	**1.5**	**2**	**3**	**2.25**	**4**
3	**0**	**3**	**-2.5**	**0**	**0**	**6.25**	**0**
4	**2**	**0**	**-0.5**	**-3**	**1.5**	**0.25**	**9**
	$\bar{r_i}$ **= 9/4 = 2.5**	$\bar{r_j}$ **=12/4 =3**			$\sum = 5$	$\sum = 9$	$\sum = 14$

From table 4, the similarity value between item **i₁** and item **I₂** can be calculated as:

$$\mathbf{r_{(i,j)}} = \frac{\sum_u (r_{u,i}-\bar{r_i})(r_{u,j}-\bar{r_j})}{\sum_u \sqrt{(r_{u,i}-\bar{r_i})^2}\sqrt{(r_{u,j}-\bar{r_j})^2}} = \frac{5}{\sqrt{9*14}} = \frac{5}{11.22} = \mathbf{0.44}$$

The above calculation is similarly done for item **I₃, 1₄, i₅** so as to get their similarity value to item **i** and the resulting values was shown in table 4b.

From table 5, we can observe that item **I₄** (the coloured column in table 1) has the highest similarity value followed by item **I₂**. Item **I₃** have a negative similarity with the target item.

Table 5. Items similarity values

Users	Similarity ratio with user a
I₂	**0.44**
I₃	**-0.55**
I₄	**0.60**
I₅	**0.28**

Also we can observe that while using the user based similarity technique, users who had rated the exact or very close number of items with the active user will in most cases have a higher similarity values with the active user compared to those that rated differently. This is not so in the case of item based similarity technique as seen in table 1, where item **I₄** had only one rating but has the highest similarity value with the target item. This is because they had the exact same rating from user **U₁** as seen in table 1. We can also make prediction of a user rating for an item using equation 2.4. We do this by computing the sum of the ratings user **u** gave to other items **j** which are similar to item **i**. Each rating is multiplied by its similarity value with target item. An example is shown below on how to predict a user rating for an item using the item based technique.

Solution

Using equation 2.4 to illustrate how to predicts **U₂**'s rating for the first item **I₁** from table 1. From our table 1, user **U₂** has rated items **I₂**, **I₃**, **I₄**, but item **I₃** have a low similarity value with item **I₁** (from table 4b). So we only consider the ratings user **U₂** and user **U₄** gave to items **I₂** and **I₅**

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$$\mathbf{P}_{(a,i)} = \frac{\sum_{j\in K} r_{a,j}.r_{i,j}}{\sum_{j\in K} |r_{i,j}|} = \frac{3(0.44)+3(0.28)}{0.44+0.28+0.60+0.55} = \frac{1.32+0.84}{1.87} = 1$$

The key disadvantages of user based and item based collaborative filtering technique is the fact that it solely depends on user or item ratings for its optimal performance and when these ratings are not available, it suffers the problem of sparsity in ratings. Other problems include cold start problems (new user or new item) and scalability problems (large datasets). One of the advantages is that it is an easy technique to implement.

b. Model-Based Collaborative Filtering

This is achieved by using the user rating to develop a model (Melville *et al.*, 2017a). It takes a complete dataset for training data or sometimes it divides dataset into ratio to train model. It recommends according to the user model developed. One good example of this technique is the matrix factorization (Yu *et al.*, 2014).

Matrix factorization is one of the most successful latent models (creates latent features to compare one user to another). As previously observed, recommender systems depend mainly on data provided in the form of user ratings or user item preferences. These ratings are arranged in a matrix form such that the column represents the items and the rows represents the user ratings on items. In most cases, these rating matrices are sparse (low rating for items) which gave birth to the idea of matrix factorization. Matrix factorization has the ability to combine both the implicit and explicit data gathered on the user and the items for the purpose of providing accurate recommendation to a user (Koren *et al.*, 2009). Matrix factorization became popular after it was used by a group of researchers in the Netflix competition between 2006-2009 (Melville *et al.*, 2017b). Where Netflix announced a prize money of 1 million US dollars to researchers who can come up with a model that can improve their RMSE value by 10%, with a given rating data of 100,480,507 ratings by 480,189 users to 17,770 items. Matrix factorization is basically used to decompose matrices and it's mostly used when we have large datasets.

The technique decomposes a matrix **R** which has a dimension **u**(users)***i**(items), into two new matrices $\mathbf{q_i^T}$ and $\mathbf{p_u}$ which contain features from matrix **R**. It does this by training (minimizing the squared error function) the set of features contained in $\mathbf{q^T}$ and $\mathbf{p_u}$ continuously until their products gives the values which are close to matrix **R** equation 2.5 (kumar Bokde *et al.*, 2015).

$$\text{Min(p,q)} \quad \boxed{\sum_{(u,i\in k)} \left(r_{ui} - q_i^T p_u\right)^2 + \lambda(\|q_i\|^2 + \|p_u\|^2)} \qquad (5)$$

Where: $\boldsymbol{\lambda}$ represents the regularization factor which control the training set and **K** is the neighbours of the active user.

$$\boxed{r_{ui} = q_i^T p_u} \qquad (6)$$

$$\text{Min(p,q)} \quad \boxed{\sum_{(u,i\in k)} (r_{ui} - q_i^T p_u)} \qquad (7)$$

Where: $\boldsymbol{r_{ui}}$ represents the value of a user rating and $\boldsymbol{q_i^T p_u}$ represents the new matrices.

This simply means that to find the rating a user might give to an item having known the features of the user and the items, we can simply find the product of matrices $\mathbf{q_i}^{\mathbf{T}}$ and $\mathbf{p_u}$ as seen in equation 2.6 (kumar Bokde *et al.*, 2015). An error function equation 2.7 (kumar Bokde *et al.*, 2015), helps in the adjustment of the values during the training which makes sure we arrive at a perfect feature matrix.

One of the major disadvantages of this technique is that it is a very expensive technique to use and some of the advantages of using includes:

i. Scalable, high performance and eradication of sparsity issues.
ii. They proved to be very essential when used in systems where the data provided are vast as they have the ability to study the data and come up with a good model which will suit the system.

Content Based Filtering technique

Content-based filtering is mainly applicable where content of items can be identified and analysed (Ghauth *et al.*, 2010). It focuses on recommending items to a user based on the content of their previously highly rated item. User and item profiles are created, which contain some special features of the item and user. Once a user preference has been identified and stored in his profile, the content based filtering finds other items in the system which have the same content as the one present in the user profile and recommend to the user.

The technique can also be applied when designing a keyword information filtering platforms like news article, web page, research articles etc. (Bocanegra *et al.*, 2017). It involves making recommendations through the retrieval of keywords from a document. In this case the content based filtering technique uses an item mining technique TF-IDF (term frequency-inverse document frequency), to calculate the weight of a keyword or frequency of a word in a document. The term frequency TF is used to capture the times a keyword appears in a document.

$$\mathbf{TF_{iz}} = \frac{f_{iz}}{max_y f_{yz}} \qquad (8)$$

Equation 2.8 (Hakim *et al.*, 2014) is the formula for calculating the term frequency of a document and it states that the TF of a document is the number times $\boldsymbol{i}$ (key word in consideration) appeared in document $\boldsymbol{z}$ (an existing document), divided by the number of times another feature $\boldsymbol{y}$ has appeared in document $\boldsymbol{z}$. To lower the weight of the commonly occurring words, we make use of inverse document frequency IDF. IDF focuses on how rare it is for documents to have the keyword and this helps us to identify how important a word is to a document as the higher the number of times a word appear in a document, the less important it is to that document.

$$\boldsymbol{IDF_i} = \mathbf{log}\frac{\boldsymbol{N}}{\boldsymbol{n_i}} \qquad (9)$$

By taking the logarithm for the value of the number of documents $\boldsymbol{N}$ divided by the number of document that mentioned the feature $\boldsymbol{n_i}$,, we can obtain the inverse document frequency IDF. The higher the value of **Tf**, the lower the IDF value and vice versa.

To calculate how relevant a feature ***w***, is in a document we use equation 2.9 (Hakim *et al.*, 2014).

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$$\mathbf{W_{iz}} = \boldsymbol{TF_{iz} \cdot IDF_{iz}} \quad (10)$$

Equation 2.10 (Hakim *et al.*, 2014) is used to identify how importance a feature is in a document. This is done by getting the dot product of the TF and IDF.

Being able to recommend an item to a user according to his unique taste, without depending on any external feature from any other user and the ability to recommend a new item to a user whose item profile has matched the content of the new item, are some of the pros of this technique. The most generally recognized disadvantage of this technique is the problem of overspecialization, which means that the system is only able to recommend the items that have a matching profile to the items the user liked previously, this reduces the possibility of a user getting a recommendation of a popular item which is not included in their user profile.

Hybrid Filtering Technique

Previously on this paper, we have discussed other types of recommender system technique. Each of these techniques have their weaknesses like the cold start and sparsity problems in the collaborative filtering technique and the problem of overspecialization in the content based technique. The hybrid filtering technique tries to overturn this weakness by combining two or more different techniques in a system design so as to achieve a better output (Melville *et al.*, 2017a), what it does in this context is that it tries to combine the strengths of different recommendation techniques so as to design systems with a better item recommendation to the user.

A good example of a hybrid filtering system is the Netflix platform which has the ability to recommend movie to a user based on the movie's feature or content which has been noticed on the other movies the user has rated highly (content based filtering). It also recommends based on the identification of users who have similar search and movie watched history, the technique assume that the users have similar taste for movies and so would love each other's watched movies. So basically the Netflix system combine mainly both content and collaborative filtering technique in order to get a hybrid system.

Hybrid filtering technique can be implemented through various means like weighted hybrid, mixed hybrid, switching hybrid, and cascaded hybrid. The most popularly used method in this literature is the weighted hybrid. The weighted hybrid focuses on finding the weight of various technique's components and then combine it so as to come up with a better design. A good example of this can be seen in a system which generate ratings based on collaborative filtering and content based filtering (or any other technique). The system finds their weights of each technique and these weights are used to determine how recommendation will be done in the system.

One known disadvantages of this technique is its complexity and implementation cost. The advantage is that it combines various techniques, thereby utilizing their strength and limiting their weaknesses.

CONCLUSION

The earliest developed recommender systems were based on filtering large portion of user's data so as to know their interest, which are then used to provide accurate recommendation to the users.

These techniques were found to have various shortcomings which have affected the quality of recommendations. This ultimately gave room for researchers to sort for hybrid approaches which initially included just the collaborative filtering and content based filtering technique but later involved some performance optimization technique like genetic algorithm, ant colony algorithm etc. These algorithms proved to be effective in performance optimization of recommender systems after evaluation was carried out. Even with what has been achieved by researchers in the performance optimization of recommender systems using various algorithms, it still remains an important research area.

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