Improved Context-aware YouTube Recommender System with User Feedback Analysis

Syed Manzar Abbas, Muhammad Usman Riaz, Asad Rauf, Muhammad Taimoor Khan and Shehzad Khalid

***Abstract* – YouTube is one of the most popular video sharing website being used by the users throughout the world. For providing ease to the user it offers a list of recommended videos every time the user searches some content. But many times the provided or recommended videos are not related to context that the user had searched. This is due to the title and the description of the videos which are although related to the keyword that the user had searched but the content of the video may be different. Moreover, the videos are recommended on the premise of users' interest irrespective of the context they are in. Therefore, the recommended videos cover different interests of the user altogether. The existing approaches are predominantly based on content and collaborative recommendations. So in this research work, the proposed and recommended approach is context based. The recommended videos are to be positioned on the basis of association and comment feedback. Moreover, for improving the quality of ranking, structural analysis (i.e. Meta information about the videos) is also performed on each video to get high relativity videos.**

***Index Terms* – Contextual Information, Context aware recommender system CARS, comments analysis, context matching, video recommendation, opinion mining.**

I. INTRODUCTION

Since 2005, YouTube has turned into a mainstream goal site for clients to discover videos and also upload their own specific videos. It is evaluated that there are more than 45,000,000 videos in collection, and that this collection is developing with an amazing ratio of four hundred and twenty minutes of video uploaded every instant of time [1]. That extremely large collection of videos can be of great interest for different clients [2]. The issues related to this extremely large amount of data is searching and exploring of trending and videos of high interest becomes a difficult thing to do. Most widely used approaches for recommendations of videos are content based recommendation, collaborative recommendation, and the mixture of these two recommendation methods as hybrid [1], [3]. YouTube has followed two types of recommendation approaches. First, from 2005 to 2010 it used collaborative recommendation system [1]. Second, from 2010 onwards it is using a Hybrid recommendation approach that has a mix of collaborative and content based recommendation [4]. Recently, the recommendation system is deployed with deep learning architecture to benefit from learning patterns through huge volume of data. Use of Contextual Information in the above approaches is another popular way of recommendation which process the recommended videos using context filter. Through this filtration, users will be recommended videos that are related to their contextual information. A user can have more than one context and have different taste of interest in each context. So, this approach CARS is very effectual to handle these distinct interests in each context [5]

YouTube provides a personalized search for the visitors and provide the videos that the user searched using the keywords that the user has provided [6]. For each video playing, related videos are recommended. On the landing page, videos similar to previous activities of the user are recommended. It has a very important role to increase chances of finding and watching related videos. The explicit feedback mechanism includes likes, dislikes and comments that may lead to a discussion among multiple users [7]. Generally the content of a video is compared based on its title, description and comments from various viewers expressing their opinions [7]. Comments are usually ignored from recommending videos, however, the comments on YouTube are developing into a very large dataset [2]. Comments play a vital role in analyzing the quality of content as they are from the view point of a viewer who can critically discuss on the relevance of the video content with the specified title and description. It is a very powerful tool to combat spam in YouTube videos [8]. However, comments themselves are effected by spam having advertisements posted by individuals and organizations [9]. They could also have negative criticism and be part of a campaign to promote or demote an agenda. Rambling arguments are posted against religious and political videos opposing their ideology [2]. Incorporating comments into the recommendation system allows the model to benefit from the feedback of the past viewers. Thus, a video may be very similar to the choice of a user but the content is either spam, fake or consisting of low quality and therefore should not be recommended to the user.

An improved context-aware YouTube recommender system is proposed that incorporate feedback analysis. Sentiment analysis of user comments is also considered in recommending videos, along with the video's Meta information. The context consists of three attributes as weekday, daytime and age, each having two values as {week/weekend}, {day/night} or {child/adult} respectively. Based on these three attributes, there are a total of 8 context sets e.g. {weekday, day, child}, {weekend, day, adult} etc. Each activity falls into one of these sets. Thus the YouTube recommendation is passed through a context filter and therefore, such videos which are highly related with the given context of the user are recommended. To improve on the appropriateness of content and their quality, the videos that have passed through context filter are associated with a

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ranking score. The ranking score depends on the desirability of the Meta information and the feedback in comments [7]. Experimental results suggest that the videos ranked by the proposed context-aware YouTube video recommendation system have higher relevance with human judgment, as compared to their existing mechanism.

In recent times, use of recommender systems for the purpose of recommending different type of content have been very popular [10]. Those content involve recommending music, videos, tourism places, and many more. These systems provide an efficient way for searching data of interest from a large collection which is increasing gradually [11]. Among different platforms of videos collection online, YouTube is one of the biggest platforms which has a very high range of viewers and video upload rate. Searching of videos which are related to the interest that includes educational information, entertainment purpose, and technical things for viewers is an important concern for them [1]. For the purpose of providing ease to the users, it recommends videos of their interest using video recommendation techniques.[12]. Initially YouTube followed a mechanism that is similar to collaborative recommendation. While later it followed a mechanism that is similar to a hybrid recommender system. Such system is a mixture of content-filtering and collaborative-filtering based recommender systems. In content filtering based recommender system, a video is recommended to a user based on the videos that the user has recently watched. Similar to the collaborative-filtering based recommendation, activities of other users are also consider and taken in recommendation process. There are two types of interactions that a user may perform on a video that are widely separated into explicit and implicit activities. In explicit activities a video is rated as liked, disliked, commented or its channel subscribed [7]. In implicit activities a video is watched for some portion before moving on to the next video. Many other type of contents are recommended through these type of recommender systems.

Using content-filtering based recommendation, a user is provided with more videos like the ones watches, irrespective of the videos watched by the other users [13]. In collaborative recommendation system, the videos that the user has liked are compared to the videos that the other users have liked. Thus, the other videos liked by users with similar profiles are recommended [1]. Considering an example of collaborative recommendation, assume that User A has watched two videos i.e. video M and video N. Video M is also watched by some other users i.e. user X, user Y and user Z. Similarly, video N is also watched by some other users i.e. user D, user E and user F. All these users have their list of watched videos. So, the videos that will be suggested to user A will be the union of all the lists of videos that are watched by users X, Y, Z, D, E, and F [12].

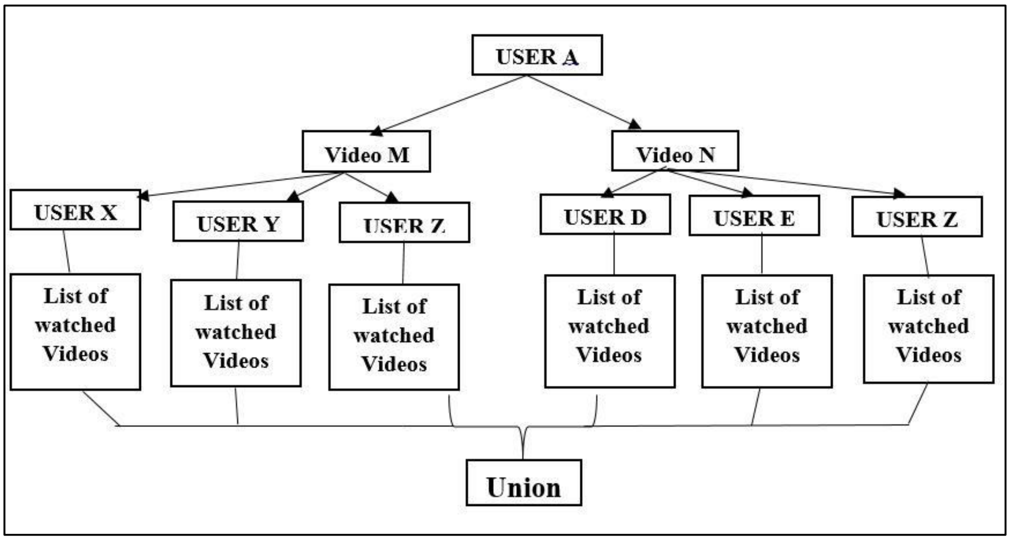

Fig. 1 Collaborative recommendation system, recommending videos to User A who has watched Videos M and N based on the collaborative analysis of Users X, Y, Z and D, E, F who have also watched the same videos.

A visual graph of this technique is shown in Figure 1. In recommendation technique using content-filtering, title and description of the videos that the user has watched in the past are compared to new videos. Videos are recommended to the user which is highly similar computed from comparison. There are two possible activities for users, as they interact with their videos of interest i.e., explicit and implicit activities. Explicit activities include video rating as like or dislike, comment, subscription etc. Implicit activities refer to watching videos but not giving any explicit feedback on it. The video may be watched fully or partially [14]. Both types of user activities are important in identifying the behavior of a user. Therefore, they both are considered in recommending those relevant unseen videos, following content based recommendation approach as depicted in Figure 2. Both techniques of content-filtering and collaborative-filtering based recommendation are used in Hybrid recommender systems. The hybrid approach take advantage of both types of recommendations and therefore, closely addresses the issue of having access to lack of data.

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II. BACKGROUND

In context aware recommendation, attributes related to a user, environment of the user, and their emotions are used to divide a users' activities in different groups. E ach context represents the attributes of the user which include mental state of user who is using the system for getting recommendations. Context is not limited to specific parameters it can be represented by different parameters which vary based upon the condition of the recommender systems. [15] The major purpose of using contextual information in recommendation is to convert two dimensional (2D) recommender systems into three dimensional (3D) recommender systems as shown in Eq. (2). Traditional 2D collaborative-filtering based recommender systems are represented through Eq. (1) [15],

$$User \times Item = Rating \tag{1}$$

Eq. (2) shows the improved version of this equation by including contextual information to develop CARS as.

$$User \times Item \times Context = Rating \tag{2}$$

where context applies filters according to the current context of the user, in Eq. (2).

Processing user comments for analysis has been rewarding. YouTube video comments are turning into a huge repository, and they can be incorporated into the video recommendation system. Sentiment analysis is performed on the video comments giving a score to the feedback that the video has got from its viewers [16]. However, comments are in various languages and not all can be included into the analysis process. Similarly, the comments that have advertisements, and spam are also filtered out. The languages that have APIs available that can help in converting the content in these languages into English. The dictionaries in English like WordNet can be used for comment analysis in English. It gives a signed score to a word representing the polarity and strength of users' opinion. For example, the string "This is nice" has a total of polarity score: 0.708. Similarly the string "This is bad" has polarity score: -1.445. Comments also have emoji's that also suggest polarity of users' opinions sometimes without any supporting words. In order to detect polarity of emoji's or emotion icons Senti-strength API is used [17]. Context-aware recommender systems assign high ranking to the given context through which the recommendation is limit to the current context of the user [18]. This improves the efficiency of recommendation by providing videos of high interest matching with context of the users. YouTube uses Gmail accounts for this purpose, to keep track of the users' activities as they browse different videos.

Existing YouTube recommender system does not maintain different user contexts. Use of contextual information in recommender systems can be used for recommending different commercial products as well. Defining a context for videos and its users can enable the context-aware recommender systems to be used for videos recommendation [5]. We have previously proposed a context-aware YouTube recommender system, however, it does not filter spam, deceiving or low quality content to sentiment analysis of the user feedback in comments [20]. Spamming has been a concern for popular online resources including blogs, forums, social media and other popular content sharing sources [21]. YouTube has a growing amount of spam videos and spam comments. Thus, the videos that may have similar title and description will have misleading content [1]. The recommender systems problems such as cold start problem i.e., limited information about new users, synonymy i.e., multiple names for a single item are discussed in [21]. Furthermore, shilling attack i.e., false reviews, limited content analysis, scalability, latency, sparsity etc. are the other related problems.

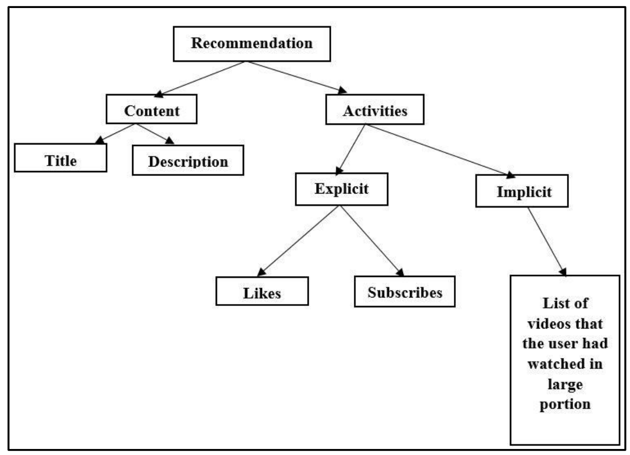

Fig. 2 A content-filter based recommender system, recommending videos based upon the similarity of title and description to the users past explicit and implicit activities

Context awareness is discussed as an effective ingredient to solve the mentioned problems via users' context. A hybrid content-based collaborative filtering approach is used for YouTube video recommendation [22]. The accuracy of this approach was reduced to recommending most favorite and most viewed videos having affected with poor metadata and video corpus size having short videos with limited user interactivity. Context information related to time, place, company and company of other people is considered to the recommender system in [23]. This helps in providing a recommendation to user with accuracy due to relevancy with users' provided information. As this technique is still under observation, the main challenges related to context aware system can be of complexity and interactivity. A study to support context aware system with the availability of polarity checking of videos is described in [24]. As conventional recommendation techniques does not have polarity checking strategy. Therefore, a weight adjustment for the checking polarity of videos leads towards an improved analysis of the users' explicit behavior. Still the challenges are of languages and wrong spelling of words. Such an example may be the use of the word good in various forms casually represented as "GOOD" or "GUD". This requires extensive use of natural language processed to

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accurately deal with such terms and improve accuracy of the model.

III. PROPOSED METHODOLOGY

A context-aware YouTube video recommender system is proposed to recommend high quality videos with appropriate Content that are also in relevance to the interest of the user in their current context. It addresses a very important issue of the existing approaches which recommends videos of a user having different interests, all at the same time. Using API of the YouTube it obtains a list of videos that are recommendable. The videos recommended for a user are separated into different groups, each defining a context of the current user. Finally, the videos from the context that the user is currently in, are chosen for recommendation. These videos further undergo a quality and appropriateness check that is carried out through Meta information analysis and sentiment analysis of comments [22]. Collectively they assign a ranking score to each video, based on which there recommended videos are ordered as priority list. It maintains a history of the user activities in their respective contexts. Working of the proposed model is shown in Figure 3. In proposed model, three attributes of a user are considered as contextual information of the user which includes age of the user, daytime (part of the day when user is using the application) and weekday (part of the week) and each attribute can further divided into two parts. Hence, the age can be child for under 18, else it can be adult. Part of the week can be weekday or weekend and part of the day can be daytime or nighttime. By this eight groups of contexts can be formed and each user will belongs to one of these groups at a time but a user can belongs to more than one groups in different times. So, every time the videos which are recommended to a user are based upon the context group to which the user belongs.

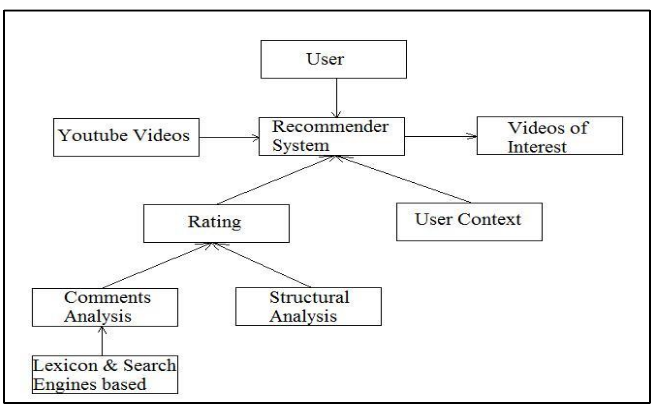

Fig. 3 Working of the model of Context-aware YouTube recommender system that support user comments analysis

With this type of approach, user will get different videos recommendation in day time as compare to the night time because of change in context. Similarly, the videos recommended on weekends are different to the videos recommended on week days. This is because a user who has viewed movies and songs would not prefer them to be recommended on Monday in office. Similarly, they would not appreciate videos related to tutorials and work on weekends. The possible contexts for the proposed recommender system are highlighted in Figure 4. The model is trained in specific to the preferences of each user based on one of the eight contexts that the user is in. When a user with similar profile is in the similar context, the videos are recommended to them. One of the possible contextual group combination can be person with age as child, part of the week as weekday, and part of the day as daytime. Different user accounts are used for providing the initial training. These users are instructed for perform various activities on YouTube from watching videos to searching relevant content. The videos can be liked by them, disliked by them or commented and they can subscribe to a channel. Through this interaction a prediction score can be generated using this data which is based upon the level of interaction or activities performed by a group of users. This things helps as a training point for the model. Very limited range of the videos from YouTube gets rated during the training phase. So, for rating the unrated videos will be done through the similarities or differences between the rated and unrated videos. Through this rating model, ratings of millions of unrated videos on YouTube can be predicted. The rating of a video is predicted using Euclidian distance as,

$$dist[(u,i,t),(u',i',t')] = \sqrt{w_1 d^2(u,u') + w_2 d^2(i,i') + w_3 d^2(t,t')} \qquad (3)$$

To compute the distance between two items with attributes given as u, i, t and u', i', t' respectively, Eq. (3). Polarity of comments is also calculated to include them in the rating of a video. The user sentiment towards a video can also prove a good resource for tuning the recommendation system. So the videos that are evaluated on prediction formula are pass on to sentiment analysis module for getting polarity of each video. The polarity of a comment is calculated using SentiWordNet. As SentiWordNet is an API that contains the polarity of most of the English words for each Parts-Of-Speech (POS) that they may appear in. It is the updated version of the WordNet dictionary [23].

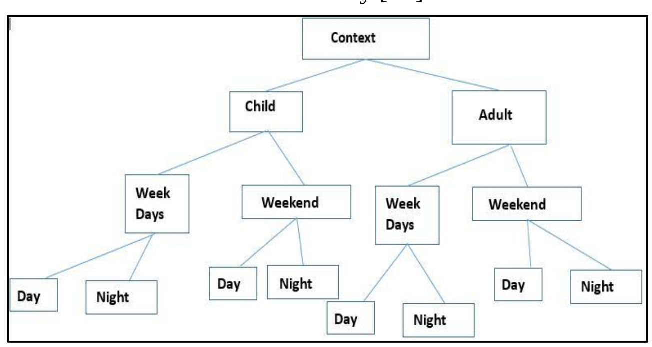

Fig. 4 Dividing of context that includes three attributes, each attributes with two sub groups forming eight contextual group

The structural information of a video is processed that may contains likes, dislikes, number of subscribers, number of comments as given in Eq. (4). The score for structural information is calculated as,

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$$Score = \frac{(w_1 \times likes) - (w_2 \times dislikes) + (w_3 \times \#cmts)}{\#Count} \tag{4}$$

Where w_1, w_2 and w_3 are the weights assigned to each attribute of the structural information. Now as we have prediction score for each video based on the training data, comment polarity for each video and the structural analysis score for each video, as in Eq. (5). Thus, the three are combined to propose a ranking formula for videos as,

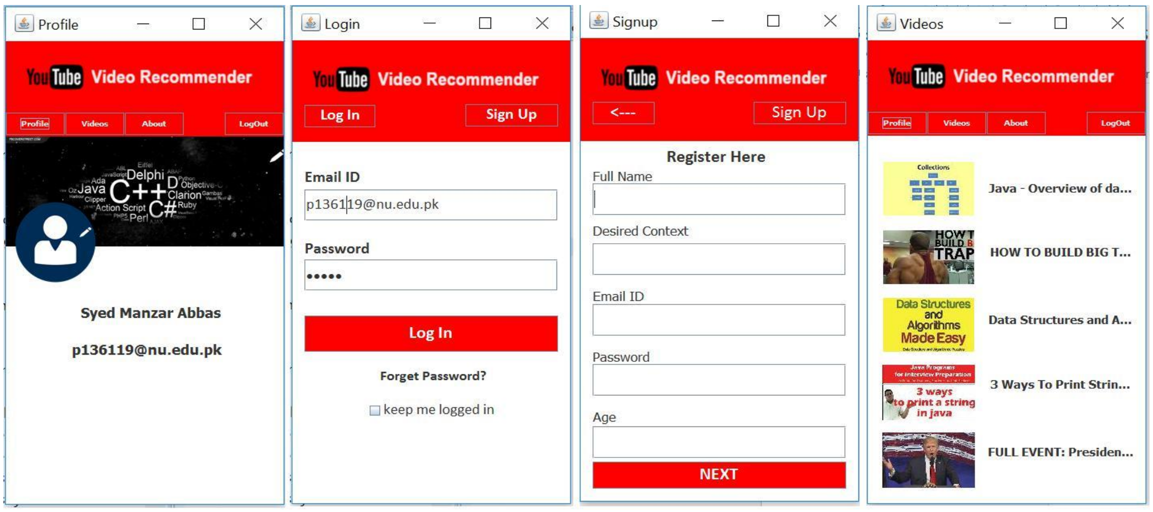

Fig. 5 Interface of the application developed with the proposed system is shown in Figure 1. It shows the landing view, login view, signup view and video

$$Score_{total} = Score_{structural} + Score_{polarity} + Score_{prediction} \tag{5}$$

This $Score_{total}$ is the final ranking of each video and is used to sort videos accordingly, for a user belonging to a specific context. Two types of scores contribute towards ranking a video in the proposed system.

They are score from the sentiment analysis of the comments as feedback from various visitors and score based on the structural information of the video. The prediction score suggests how other users with similar profiles have responded to this video, when they were in the same context as is the current user. Based on these parameters a ranking score is associated to a video. The videos are sorted in decreasing order of their ranking scores. Structural information for the videos is included in calculating the ranking score of a video. Figure 5 shows interface of the Application developed.

It shows IDs of the videos for uniquely identifying them in the first column. The second column has video titles while the next two columns have the number of likes and dislikes that the videos has received. The final two columns have the number of comments and views of the video.

IV. EXPERIMENT AND RESULTS

The videos in Table I are considered for initial analysis as presented along with their titles and structural information based on user's explicit feedback. For example, the first video is liked by 944 users while disliked by 16 users and has a total of 119 comments when watched by a total of 76,772 users. Please note that the videos listed are based on the activities of the users who participated in evaluating the proposed model as compared to the YouTube existing model. Table II has ordered the videos as they were originally ordered by YouTube. However, the proposed model presents their different ranking schemes for presenting these videos. In case of considering only the structural information, the video at the end would be presented at the top of the order. Similarly, ordering videos according to sentiment analysis of their comments, the second video should have been at the top of the list. Predicting the appropriateness of the videos through the context filter again places the first video as the most desirable by the user. The final column shows the prediction of the videos as suggested by the formula in the proposed model which make use of the three different types of predictions and aggregate them as mentioned in the last column. According to the final score, the videos should be ordered as first, followed by third, then second and then the fourth and fifth video. For the sake of fair comparison, the videos that were filtered due to not matching the context were also removed from the videos recommended by YouTube. Filtering the videos based on their context and ordering them based on the total score as proposed by the model closely address to the needs of the users.

These videos undergo structural and comment analysis according to the mechanism specified in the above section. The variation in the order of the recommended videos with the given structural analysis, comments analysis and both combined suggest how videos may be more desirable in structural information but have bad feedback in comments and vice versa. Therefore, a mix of the three types of analysis gives a desirability score to organize recommended videos. Only a small number of videos are considered for the sake of demonstration.

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TABLE 1. VIDEO IDS AND TITLE WITH THEIR STRUCTURAL INFORMATION

ID OF THE VIDEO	TITLE	LIKES	DISLIKES	No. of Comments	Views Count
A71aqufiNtQ	React JS Crash Course	944	16	119	76,772
rQVHPOFMUdI	Advanced C++ DirectX Game Programming Tutorial: Lesson 2	170	10	15	24,784
-CpG3oATGIs	C Programming Tutorial | Learn C programming | C language	4872	146	355	516,258
sBZkj6rGLj0	Add inches to your BICEPS with this routine! BBRT #7 (Hindi / Punjabi)	14,705	388	689	880,884
JKpeIxh4ScY	Samsung Galaxy: The Rest of Us	72,782	17,304	7,987	4,767,094

TABLE II. THE VIDEOS TABLE ORGINALLY PRESENTED AS ORDERED BY YOUTUBE WITH STRUCTURAL SCORE, PREDICTION SCORE AND TOTAL SCORE

ID of the Video	Video Title	Youtube Ranking	Structural Score	Polarity Score	Prediction Score	Total Score
A71aqufiNtQ	React JS Crash Course	1st	0.0014757375465	3.01136984139192	0.5	3.512845578938494
sBZkj6rGLj0	Add inches to your BICEPS with this routine! BBRT #7 (Hindi / Punjabi)	4th	8.2652008858E-4	0.19954545454545	0.4	0.40037197463404896
rQVHPOFMUdI	Advanced C++ DirectX Game Programming Tutorial: Lesson 2	2nd	8.0866890493E-4	0.12333333333333	0.3	0.42414200223827113
-CpG3oATGIs	C Programming Tutorial | Learn C	3rd	7.3414214421E-4	0.0763369435805	0.2	0.277071085724757
JKpeIxh4ScY	Samsung Galaxy: The Rest of Us	5th	0.0016987193375	-0.568181818181	0.1	-0.566483098844235

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Enhancement of the recommendation system can be defined by a comparison between the videos searched by a user for different keywords. The results in form of videos from YouTube are extracted using its API. The search terms are Fast and Furious and Punjabi movies whereas video titles and their metadata are given in Tables II and III. For the sake of simplicity in visualizing the case, only 5 results are considered. The ranking by the YouTube of these videos and proposed model for their respective search terms are given. As the purpose of this research work is to improve the users' experience for YouTube by recommending such content which belongs to their interests. These results were examined by human judges who have knowledge of keywords which were provided as search string. For the purpose of evaluating the subjectivity of the model, Judges observe the video content that were recommended and compare them to their ordering. As the number of videos which are enough for the purpose of evaluating the performance of the recommendation and their effectiveness are not know, Hence, Precision can be used for including number of videos in evaluation that can be Precision @ n (or p@n) for n= 5, 10, 15 and 20. Here n represents the number of top videos recommended by the two systems. The proposed model achieves higher desirability of recommended videos with on average 12 out of 15 and 16 out of 20.

On applying structural analysis on the given videos, the system has extracted the attributes of the videos which include likes counts, dislike counts, comment counts and the number of viewers for each of the videos separately. After this, the formula which we discuss previously was applied to calculate the score. On applying comments analysis, the system extracted the comments of each video and then using SentiStrength to calculate the polarity of the video. We had already discussed this technique in detail. Once both the scores has been calculated for each of the videos then the comment analysis score of a video will be added with rating analysis score of that video. By this, each video will get a new score and that score is used for the ranking purpose. The tables in appendix gives a comparison of the videos recommended by proposed approach along with the YouTube standard recommendations.

V. CONCLUSION

YouTube is considered as one of the biggest online video collection platform that is progressively growing into a large corpse of video collection. Among different video collection platforms that are having large amount of data, competition exist between them and only those platforms will retain for longer that fulfill their users demands in efficiently. Till now YouTube follows an approach which is hybrid of content-filtering and collaborative-filtering based recommendation for recommending relevant videos to the user. Although it does not involve contextual information in recommendation process which is very important for enhancing users' experience. Our proposed model will works on the top of YouTube, it will obtain video data from YouTube by using its API. It will maintain the contextual information as a history of each user for recommending relevant videos. Moreover, for ranking a video, dictionary based sentiment analysis of specific comments (that can be English comments and top rated comments) is performed to compute sentiment polarity of the videos. Observers decided that the proposed model recommends more relevant videos and better ranking with respect to the existing techniques and approaches

In future the context parameters can be extended have mor e specialized context groups. Similarly, languages other than English can also be considered for analysis.

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