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# Design of Context Cluster and Load Balanced Video Recommendation System in Cloud Computing

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## ABSTRACT

Nowadays, in online social networks, there is an instantaneous extension of multimedia services, and there are huge offers of video contents, which have hindered users to acquire their interests. To solve these problems, different personalized recommendation systems have been suggested. All the personalized recommendation systems which have been suggested are not efficient and they have significantly retarded the video recommendation process. So, to solve this difficulty, context extractor-based video recommendation system on cloud has been proposed in this paper. Further, the system has server selection technique to handle the overload program and make it balanced. This paper explains the mechanism used to minimize network overhead, and recommendation process is done by considering the context details of the users; it also uses rule-based process and different algorithms used to achieve the objective. The videos will be stored in the cloud and through application videos will be dumped into cloud storage by reading, coping, and storing processes.

## KEYWORDS

Cluster, Context, Load Balance, Multimedia, Online Social Networks, Server Selection, Video Recommendation

## 1. INTRODUCTION

Multimedia has become the resounding concept in the current social networks and it is providing a large number of videos so the users are finding tough time to capture their related interests on the quick basis. Despite that present recommendations are always not explicit and are not well aimed with the interests of the end users. Recommendation is anticipated to be one of the vital services that can give such customized multimedia contents to users. (Wang et al., 2013) The privacy of users' factors

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and video service marketers' stores, which are of remarkable value and are very fragile maintaining these are a huge problem with the existing proposals.

Existing Collaborative filtering(CF) recommendation system calculate on content acceptance and ample user transactions histories, this system depends upon adequate history consumption report and assessment which won't be befitting real-time recommendation. Content based filtering (CB) recommendation systems mainly target the affinities of tags, titles of contents, descriptions and rely on the user-interest things based on the individual reading history of end-users. Even though the deployment of such a recommender system is easy. Nevertheless, just using a bag of words depicting the profile information of a user is not pleasing users to acquire their exact interests. Next building a graph to take account of similarities between the recommendation items comes under graph-based recommendation systems (GB). Here the node selection problem turns into a recommendation problem, apart from that based-on user's sentiment, behaviors and friendship forming a graph in social networks. Even merging graph theory with the recommendation is a fabulous idea but it won't be acceptable or convincing because graphs should be changed continuously.

At present, there is no context based video recommendation system in social networks. Most of the current work allocations systems are based on equal job allocation which will not be efficient when the job durations are very high. The majority of online social network video recommendations is based on the number of times the video is watched and it is common to all users Immaterial of their age, profession, location. This type of recommendation is not convincing users all the time, people in one region might like to watch videos related to their region even though numbers of clicks are less than very popular videos. So, this paper introduces context extractor based video recommendation on cloud.

To make the task easier, we suggest a cloud based video recommendation system. The system which studies cluster behavior of the end user rather than individuality will help reduce network overload and increase recommendation speed and accuracy. To avoid network explosion, the users will be clustered into various clusters using certain clustering rules based on user context details that are collected on video-sharing online platforms. The proposed approach will have high precision, high recall and a low response delay.

Advantages:

- Efficiency of cloud storage
- No same videos are recommended
- Video selection strategy based on cluster ids
- Proper performance guarantee
- Reduces network overhead

## 2. LITERATURE SURVEY

(Guo etal., 2021) exhibits a plethora of technically related cloud services available in the cloud computing world. Furthermore, user specifications are subject to modification. As a consequence, recommending programmes that meet the needs of consumers is challenging. To address the issues, a requirement-based service recommendation approach is proposed. To minimise the recommended selection, first shape user communities by clustering. Second, estimate user QoS requirements using the recorded QoS (Quality of Service) values and the measured QoS values. Third, the degree of user-to-service matching is determined based on the specifications. Finally, we can create a list of service recommendations for the target user based on the similarities between the target user and the user's neighbours, the disparity in their matching degree of service, and the ratings of services by the neighbours. Our system outperforms the conventional collaborative filtering method and the deviation-based method in terms of recommendation accuracy without sacrificing performance. Video background music, as one of the traditional forms of entertainment, has increasingly shifted from traditional to network consumption, posing the issue of information overload. In terms of model design and auxiliary data.

(Kai et al., 2021) proposes a tightly coupled fusion model based on deep learning and collaborative filtering to solve the problem of low prediction accuracy in the scoring prediction problem due to sparse matrices. In the use of auxiliary information, compensates for the model's sensitivity to the sparsity of the score matrix from a data perspective by using crawler technology to collect auxiliary information on the user side and the video background music side. In terms of model architecture, it performs auxiliary information mining based on the diversity and structural differences of auxiliary information, learns user preferences using an improved stack auto encoder, and mines secret features of video background music using convolutional neural networks. The closely coupled fusion of multiple deep learning models and collaborative filtering is realized using the concept of probabilistic matrix decomposition. The collaborative filtering process is supervised, and the optimized prediction result is finally obtained, by taking into account the user's interest and video background music characteristics. The system's performance and feature tests were conducted to check the hybrid recommendation algorithm's efficacy and the system's impact on recommendation, respectively. According to a rough experimental study, the algorithm built will increase recommendation quality and achieve the desired result.

(Karim et al., 2020) introduces video quality analysis (VQA), which assesses the complete range of reference metrics while taking into account quality degradation. Experiments on various social clouds (SCs) and low-quality videos are carried out as part of the study. Selected videos are submitted to SC to determine video service and quality discrepancies. The peak signal-to-noise ratio (PSNR) of all videos (Avg 100) has no effect on other indicators, according to WeChat. As a result of the experiment, WeChat appears to offer the highest video quality and multimedia facilities to its users in order to satisfy Quality of Service (QoS)/Quality of Experience requirements (QoE). Cloud computing is a modern method of storing data in which users upload video data to cloud servers rather than making duplicate local copies. However, it keeps the data out of the hands of consumers, who would usually access and handle it.

(Liu et al., 2018) use to work on how to ensure the quality and reliability of video data stored in the cloud for the provision of video streaming services to end users becomes a major concern. In the context of cloud computing, this paper examines the specifics of the authentication methods for the integrity of video data encrypted using fully homomorphic cryptosystems. Specifically, using the method of block tags, applied dynamic operation to video data stored in the cloud, enabling the data's integrity to be successfully checked. The entire procedure is based on a study of existing Remote Data Integrity Testing (RDIC) techniques.

(Yiqi Fu.et.al, 2018) Proposed on the neighbor based strategy is the development of closest neighbor chart which is intended to uncover steady and well known competitors, also, the decision of making forecasts in a specific request, which applies needs to different competitors as opposed to crossing up-and-comers in arbitrary to advance the final exactness. Box a bunch of tests on a genuine appropriated administration quality dataset WS-DREAM for invigorating the fog cloud environment, approve the practicality of our technique in terms of administration suggestion exactness and confirm the inspiration that NearestGraph can get a decent exhibition in huge fluctuation of QoS properties.

(Kristofer R. Smith.et.al, 2018) Propose CloudEdge, a calculation table also, programmable remote access network engineering that misuses in-network calculation capacities to give unified information preparing and transport administrations to end clients. To address the multiresource the executives challenges, for example, remote data transfer capacity and calculation power that emerge in incorporating in-network administrations for video content conveyance, we figure a system that streamlines the nature of involvement of various video transfers, subject to remote transmission.

In the disseminated cloud environment (Yanwei Xu.et.al, 2017), a cloud stage is frequently not willing to share its recorded client administration conjuring information with other cloud stages because of protection concerns, which diminishes the attainability of cross-cloud synergistic administration suggestion harshly. Also, the client administration conjuring information recorded by each cloud stage may refresh over the long run, which lessens the proposal versatility essentially. Considering these two difficulties, a novel privacy preserving and versatile help proposal approach in light of SimHash, that is, SerRecSimHash.

(Yonghua Xiong.et.al, 2016) Trial results show that the current technique as it utilizes 17% of the capacity hubs in typical state and takes 8.3% normal working time with twelve arrangements, coming about in more energy productivity than the full heap of conventional HDFS strategy and about half heap of the Stanford improved HDFS strategy. Furthermore, the technique is not difficult to execute also, unquestionably offers certain application esteem. The strategy shows the accompanying benefits:

1. It is exceptionally intended for a CVS (Cloud video surviellence) framework and is not difficult to embrace broadly and convey for different frameworks including distributed computing, cloud plate, or other portable applications, for example, versatile UGC (User generated Content) also, portable notice.
2. It can meet the presentation prerequisite while limiting energy utilization.
3. Compared with customary and Stanford improved HDFS techniques, the proposed approach demonstrates its prevalence and adequacy. The Recommendation System assists people in making decisions about an object or an individual. The growth of the internet and e-commerce has fueled the creation of recommendation systems. The scalability of the recommendation framework is hindered by the large volume of data. One of the solutions to this problem is Hadoop. (Kumar et al., 2015) presents Mahout, an open source java library that favors collaborative filtering in the Hadoop setting. Collaborative filtering is a machine learning algorithm. The paper describes how a collaborative filtering recommendation framework can be applied in the Mahout context. The approach's success has been demonstrated using Speedup and productivity.

(Samuel et al., 2015) clarifies as, to engage a client rather than a framework head to set clash free policies for their online interactive media information an approach is displayed where security prerequisites are put away in a control framework and a structure of piece and requirement rules for the policies are made. The utilization of such a framework requires the strategies to be set mindfully. This paper also presents some approaches for the authentication for privacy concerns to guarantee preciseness and lucid stability to secure sensitivity and sharing of multimedia contents in private mode.

(Cheung et al., 2015) explains, accessing social graphs to discover user connections are available as a paid service. An easier alternative way is to massive data a user generates by sharing images on the social platform. Here they have investigated several images which are shared by users from different social networks to find similarities which are very helpful for the recommendation.

(Jiang et al., 2014) – which facilitates POIs recommendations for social media users. They developed an approach for user preferred topics such as cultural, cityscape, landmark to be extracted from geotag refined by textual descriptions of photos instead of getting the data only from GPS. Existing collaborative filtering (CF) recommendation system calculates on content acceptance and ample user transition history, this system depends upon adequate history consumption report and assessment which won't be befitting real time recommendation. In this paper, topics which have more preference can be fetched from the documented explanation attached with a person's photo through author topic model and also travel area and used topics inclination prompted instantaneously. Instead of geotags, user topics, and travel topics which are similar or ranked using POI's based on the past work. According to likeliness of preferences of the user topic, mining of similar users can be done.

(Tekin et al., 2014) explains a decentralized successive basic leadership on disseminated online recommender framework. Suggestions depend on client look questions refined by their particular foundation, including history of purchased things, sexual orientation and age all of which offer setting to the client. In this paper, the recommendation is based on the history of items and based on user search query which will be used as context information and they have specified the advantages of decentralized recommender systems over centralized. (Wang et al., 2013) have introduced the key concept and the structure of social media recommendation, which explains, in social media it takes following from both users and content that is why recommendation is required and what unique information is needed for operative social media recommendation. They have also specified major perceptions and theoretical formulation on the social recommendation system.

(Tkalcic et al., 2012) gives idea based on the user's facial emotion expression they have proposed a approach for the unremarkable hidden classification of images with affective labels. So, developed effective labels which are in comparative study of a CBR system for images. Nowadays in online social networks, there is an instantaneous extension of multimedia services and there are huge offers of video contents which hindered users to acquire their interests. To solve this problem, the authors in paper (Zhou et al., 2016) suggested a different personalized recommendation system.

(Li et al., 2011) explain that News articles recommendation takes a pledging path for research. Because, around the world the real time information has fast access as its projection comes from several sources. By the benefits of the user and the information of the news content, the customary systems have attempted to become accustomed to their services to the individual users. Though, the undeveloped relationship among diverse news report items, and the exceptional properties of innovative articles, such as short shelf lives and value of imminence, judge that previous methodologies unproductive. This paper introduces the two-stages scalable approach which is efficient compared to the existing new article recommender; this approach takes the two levels and contemplates high-class properties for the recommendation. They have presented the selection of the news centered on fundamental property of interest of the user.

(Wang et al., 2010), explains building a graph to take account of similarities between the recommendation items comes under graph-based recommendation systems (GB) here the node selection problem turns into a recommendation problem, apart from that based-on user's sentiment, behaviors and friendship forming a graph in social networks. Even though merging theory with the recommendation is fabulous ideas but it won't be acceptable or convincing because graphs should be changed continuously.

(Machanavajjhala et al., 2011) explains that with the current surge of informal organizations, for example Facebook, new types of suggestions have turned out to be conceivable- proposals that depend on one's social association altogether to make customized suggestions of advertisement, content, items and individuals. Since suggestions may utilize touchy data, it is theorized that these suggestions are related with security threats. The principle commitment of this work is in formalizing exchange off between exactness, furthermore security of customized social suggestions. Daily many video clips are shared on the applications of online social networks and multimedia sharing websites which includes the videos which are replicas of one another, quite dissimilar, interrelated or alike. So, confronting such billions of web pages' online end users will face hardship to find their interests. Many different video recommendation systems have been suggested but they are not always accurate and consistent for users. Multimedia platforms like YouTube, social Networking sites like Facebook have been flooded with a large number of videos being uploaded by users every second of everyday. Some of these are duplicates, similar, related or sometimes entirely different. According to a claim by youtube they add 300 hours of videos every minute. With this huge amount of data users might find it extremely difficult to find the content they are looking for. To tackle this situation, platforms have created a recommendation algorithm that works on video categorization, video illustration labels or watching history. These algorithms are still highly imprecise and not always stable with interests of end users'. Some websites also provide users with a search engine that helps users to reach their desired content quickly but they are not always convincing.

They have following disadvantages:

- Inconvenient to reiterate video-label modules.
- Lack of scalability in dedicated servers.
- Illustrates the difficulty of the task is illustrated due to unlikeliest and noise inherent to data recommendation based on click rates.
- It will recommend the same video for all users.
- There is no context based recommendation.

(S.baluja et al., 2008) multimedia platforms like YouTube, social networking sites like Face-book have been flooded with a considerable number of videos being uploaded by users, every second of every day. Some of these are duplicate, similar, related or entirely different. According to a claim on Youtube, they add 300 hours of videos every minute. With this, a huge amount of data users might find it extremely difficult to find the content they are looking for. In this paper, to provide personalized suggestions of the videos in this paper they have created a user and video graph and have analyzed it and some simple method they have used to go through the various graphs and find out the preference and named it as absorption and have used the random walk.

(Billsus et al., 2007) explains, Content Based filtering (CB) recommendation system mainly targets on the affinities of tags, titles if contents, descriptions and rely on the user-interest things based on the individual reading history of end-users, even though the deployment of such recommendation systems is easy. Nevertheless, just by using a bag of words depicting the profile information of a user is not pleasing users to acquire their exact interest. The current recommendation system has a normal in which the user network system is the web app. A brief list will be presented to the user by a system in the form of a list like drop down, the user can select any item from the list to explore it or to understand it well and to know more details of that item, this type of recommendation is common. This paper introduces the alternative for recommendation of items and mainly focuses on the content based recommendation system. The common items will be shared by taking into account user likes and dislikes, their reviews, users' interests by comparing all of these with different user profiles and the analyses of the items which are related to user interest.

## 3. DESIGN AND IMPLEMENTATION

### 3.1 Module Description

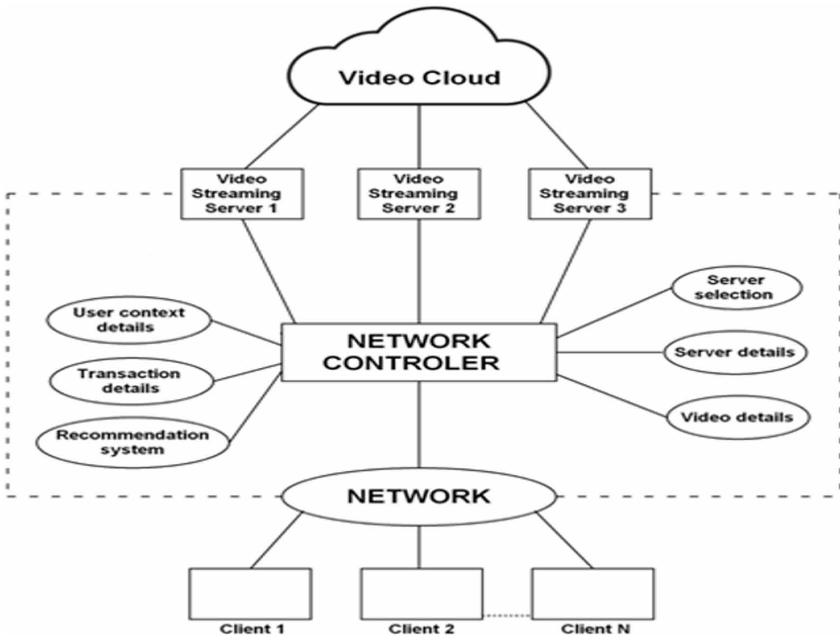
As mentioned in figure 1, there are many modules and the description is as follows: Video streaming process using ftp.

As an effective and efficient way to provide computing resources and services to customers on demand, cloud computing has become more and more popular. For effective use of the cloud storage using the social network on the cloud computing we have demonstrated on the video based file system. Using the Video steaming process, we are uploading our data on the cloud storage server. To send the data to the cloud storage server we use the ftp (File transfer protocol) has been used to stream the videos. While downloading the video data from the cloud storage server we use the streaming technique to display the video to the client.

### 3.2 Context Clustering

In this module context details are taken into account, here in this project context details include age, profession, location. The users having similar context details are grouped into one cluster, each cluster will have a unique cluster id. Users with the same cluster details will be grouped with some unique cluster id. Recommendation process can be done using this.

**Figure 1. Architecture depicting Video Streaming**




### 3.3 Recommendation Rules

When a user has registered with his context like location, age, professionals, according to his context id, the server will check the context clustering id based on this context clustering id it will list the video which is recommended by the same clustering id users from the social network.

### 3.4 Server Load Balancing Module

When the user clicks on the video he is interested in, the service request goes to one of the servers, and the requests will be placed in a queue before those are processed by any of the servers. Since a multi-server system will be able to maintain a large number of requests so they will be placed in a queue. If the server is free the requests are processed quickly or else they are placed in a queue one after another, until they are handled by one of the available servers. Here FCFS (first-come-first-serve) queuing is applied here.

### 3.5 Context Cluster Algorithm

Context clustering refers to the grouping the similar context details into by assigning unique cluster id. First it takes the three context details in the array form separately, initializes all these arrays with different data then follows the step as shown below:

```
Step 1:  Let Age_ Groups is an Array for various Age Groups. Ex:
         15 – 20, 21 – 25, 26 – 30.
Step 2:  Let Location [  ] is an Array for various cities EX: B, H, C
Step 3:  Let Profession [  ] is an Array for various Professions.
         Ex:  IT, Dr, CA
Step 4:  Initialize all the three Arrays with relevant DATA
Step 5:  Let Assume Numbers of items in AGE – Groups and Location,
         Profession is X, Y, Z.
```

```
Step 6:  Number of unique cluster is N. Which is Calculated as N =
         X * Y * Z. CN = 1
Step 7:  For I = 1 To X
Step 8:  For J = 1 To Y
Step 9:  For K = 1 To Z
Step 10: Cluster [ CN ] = AGE – Array [ I ] + CoC [ 1 ] + PRO [ 2 ]
Step 11: Next Continues K,I, J
Step 12: Stop
```

### 3.6 Recommendation Rules

When a user has registered with his context like location, age, profession, according to his context details, the server will check the context clustering id based on this context clustering id it will list the video which is recommended by the same clustering id users from the social network.

```
Pseudo code.
Step 1:  User is logged in with authenticated User id and password.
Step 2:  Lets Users having Age is 'a[]', Professional p[],Location
         l[] of Array.
Step 3:  Initialize variables I, J, Z, Cluster ID is 'CID1' and N
         is Total Number Combination Cluster;
Step 4:  Get the user Age, Professional, Location from Register details
Step 5:  Search CID1 of the user.
            For I =0, J=0and Z=0  to N
            CID1= a[I] + p[J] +l[Z] for matching cluster id,
Step 6:  Let Videos Transaction be VT which is viewed by all
         cluster id users with respect to their Cluster ID CID2.
Step 7:  Select all VT belongs to CID1,
            If CID1 is equals to CID2 then
            Short List all Video 'V' with same Cluster ID
Step 8:  Sort video According to most watched from Top and neglect
         the one time watched videos.
Step 9:  Recommend the shortlisted Video to User belonging to the
         same cluster ID.
Step 10: Watch Recommend videos.
```

### 3.7 Modules

#### *3.7.1 System Implementation Design*

Member user is an end user who can register by themselves. Once they are registered each user will have a user id and password, by which they can enter into their session and start watching the video.

Whenever the member is watching the video, details will be stored in server DB which will be used in the Recommendation process.

```
Admin session
       Login
       Age Group (View, Edit)
       Location (View, Edit)
       Profession (View, Edit)
       Create Cluster
       Change Password
```

```
User session
        User Registration
        Login
        User Profile Management
        Video File Upload
        Play Video File
           a. Select the Category
           b. Select the Video to play
           c. Server Selection using Load Balance
           d. Fetch the video from cloud storage
           e. Stream the video to user system thru selected Server
           f. Gather Transaction Details
        Video File Recommendation System
           a. Context Collector (Location, Age, Profession)
```

## 4. RESULTS AND INFERENCES

Figure 2 shows the homepage of a cloud based video Recommendation System. One has to register by providing a userID, password which is created in the registration form.

Figure 3 depicts the login page, where a person can login as admin or as a user for the application, by providing required information such as user_ID, age, contact number, etc.

Figure 4 shows the login form for the admin, where the admin can login into his account by providing his ID and password. Figure 5 depicts the various options that the admin can perform, such as creating clusters, viewing his profile, viewing server details and context details.

Figure 6 shows the context cluster creation tab for the admin, where the admin creates the cluster based on context.

Figure 7 is the list of data stored in the database, these data are the results of context cluster creation. Once the creation of the cluster is successful the pop-up message will appear on this page.

**Figure 2. Registration form of User**

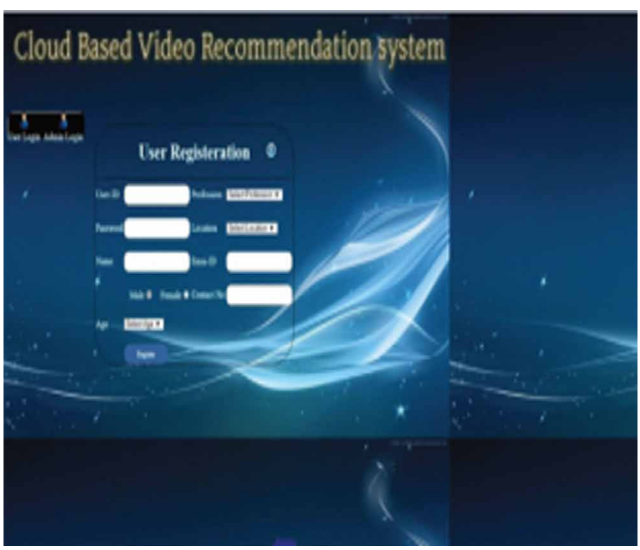


Figure 3. Login form for User

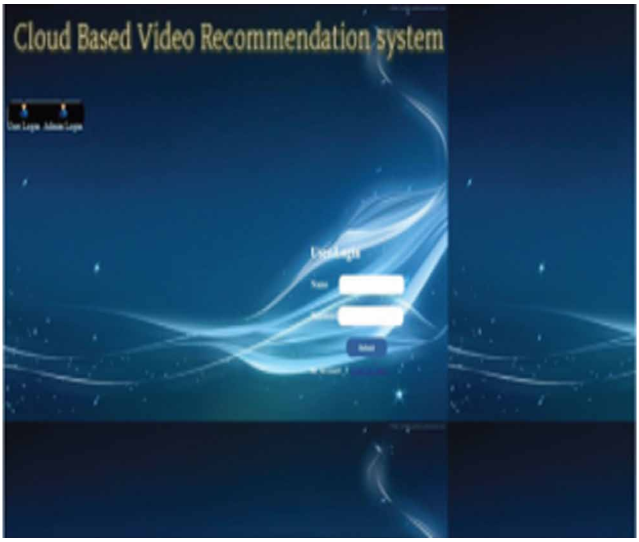



Figure 4. Login form for Admin

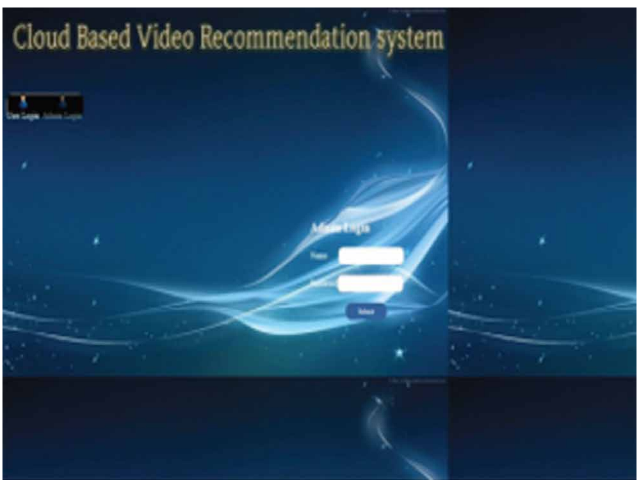



Figure 8 shows the server details of the system. Where Admin can see the details of the user as shown in Figure, server details consist of ID, name and IP port. Here admin can view user age, name and other details.

A user can view his profile by signing in into his user account as shown in Figure 10. Here all the details provided by the user can be viewed by the admin. The above Figure shows how a file can be loaded to the cloud. Here one can provide the title for the video which he is uploading.

The Figure 12 shows how one can select the video based on whether it is public or recommended. An uploaded can be viewed or played as shown in the above Figure 13.

Figure 14 shows all the details of the uploaded video in the database. Figure 15 is the snapshot of the database in which all the user list is stored along with other details that the user has provided while signing up.

**Figure 5. Admin can create clusters; view his profile, server details, context details**


**Figure 6. context cluster creation tab**

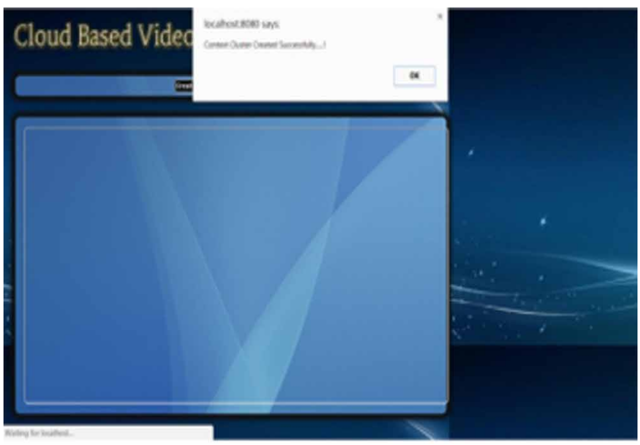



**Figure 7. Results of context cluster creation**

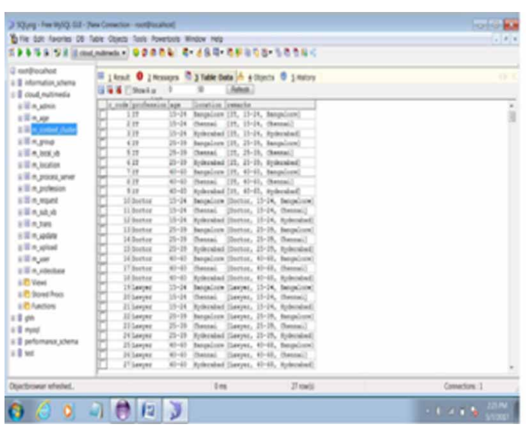


Figure 8. Viewing Server details

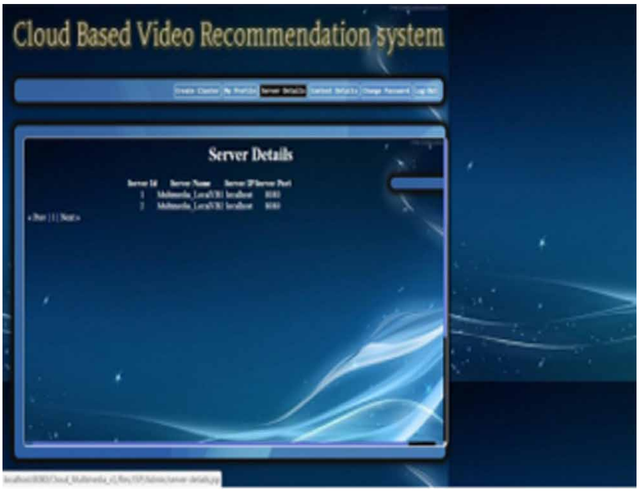



Figure 9. Viewing Context details

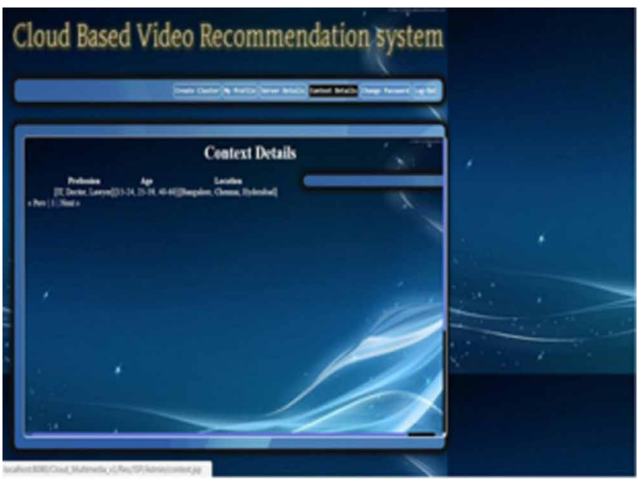



Figure 16 shows the category of views along with age and name of the video. It is helpful to analyze file names that are stored in the column of the database. Figure 17 depicts the server that has been used while the videos played by them. It also shows the cluster playing the videos by the users. Here server id and the trend of the viewer and their age group.

The Figure 2 shows the home page of the application which consists of user login and admin login. When the admin opens the application, he will be landed on the homepage he has to login. When the admin clicks on the admin login button admin login form will open as shown in Figure 3. When an admin logs in he is able to create a cluster, view his profile, server details, contact details as shown in Figure 4. Figure 5 shows the context cluster creation tab in the admin module. Admin can create the cluster based on context and Figure 6 shows results of context cluster creation which is a table stored in a database. Figure 8 describes admin viewing server details and Figure 10 displays admin viewing context details. Figure 7 shows User login form, if a user wants to create an account he can click on the sign up option in the user login form, when he clicks on signup option it redirects

**Figure 10. Viewing user profile**

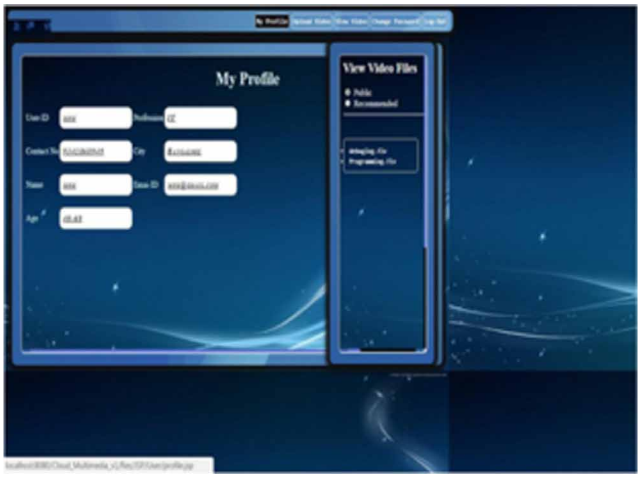
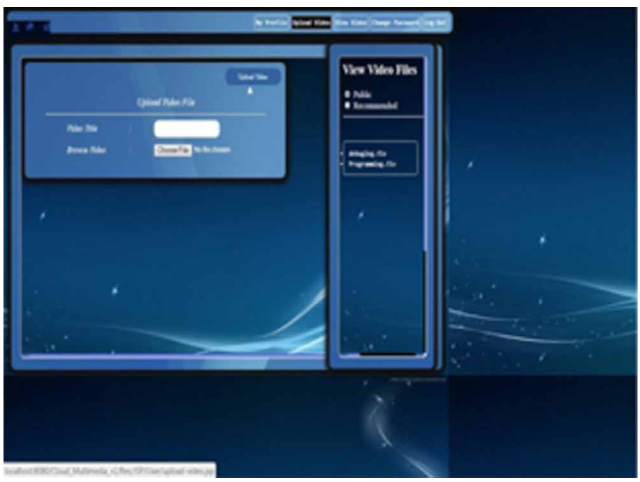



**Figure 11. Uploading file to cloud**




to user registration form as shown in Figure 8 where user has to register by giving his contact details. The user can use his own profile which is shown in Figure 10. The process of uploading file to the cloud is displayed in Figure 11. Figure 12 shows the watching videos by users which consist of two repositories public and recommended. Figure 13 showing changing password of user by him-self. Playing and viewing videos can be seen in figure 14. The admin details will be stored in a database which showed in Figure 15. Figure 16 shows the one of the contact details named age, where age groups we have grouped for the project is shown here. Figure 17 shows the details of uploaded videos, when the user uploads the video it will be stored in cloud and details will be stored in a database here. Figure 18 displays the entire users list along with their details, when the user registers the details he gives will be stored in the database as shown in this Figure. Figure 17 shows video transactions which mean it includes the details of both video and user who has played that video, it shows the cluster code of the user, his is, and name of the video file played which will be stored in tabular format in the database. Displays server used while playing video since the application uses a multi-server system

Figure 12. View videos

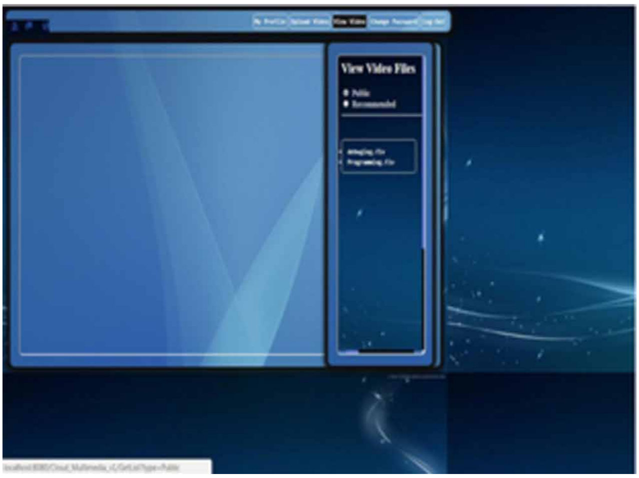
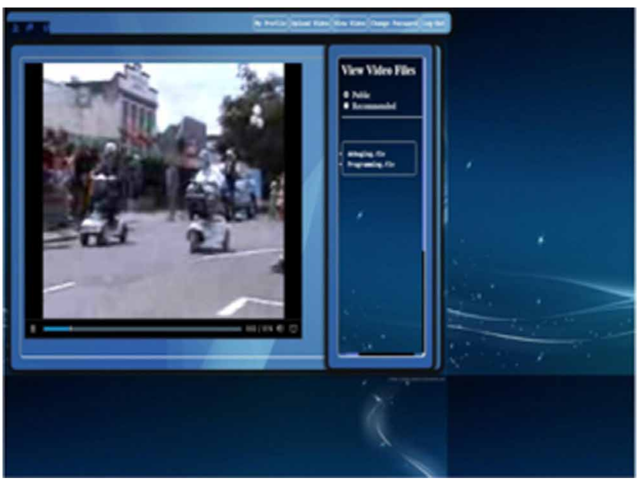



Figure 13. Play and View videos




there will be two servers used in the application if one server is busy the video will be redirected to the server which is free to reduce the network overhead. This Figure shows the server_ id and which video is played in each server.

## 5. CONCLUSION AND FUTURE SCOPE

Presented a system which is context based video recommendation with multiple servers. A user is categorized based on his attributes and Video Recommendation is done based on these attributes. Tested this system with one gateway server and two video streaming servers the video files are stored in real cloud storage. Our experimental results show that this system meets all the functional requirements. It is a web based application developed on MVC Architecture.

The proposed system follows algorithms such as context cluster algorithm and recommendation rules. This work also includes the server load balancing mechanism which explains when the user

**Figure 14. Details of uploaded videos**

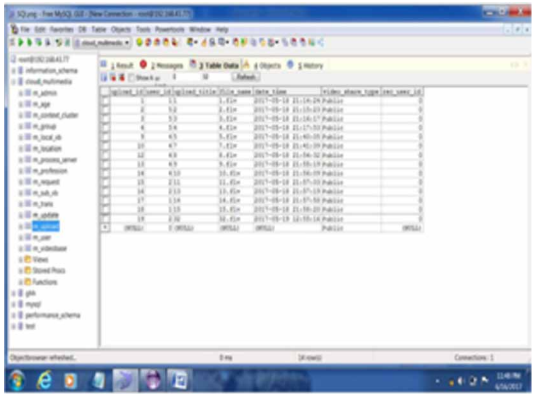


**Figure 15. All the users list along with their details**

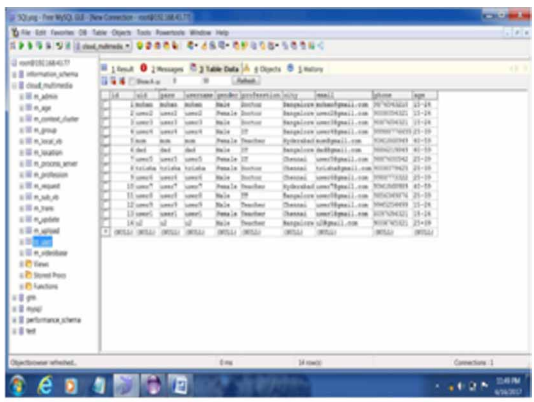


**Figure 16. Video transactions**

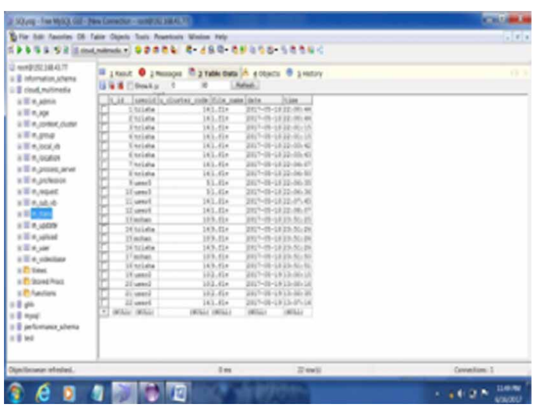
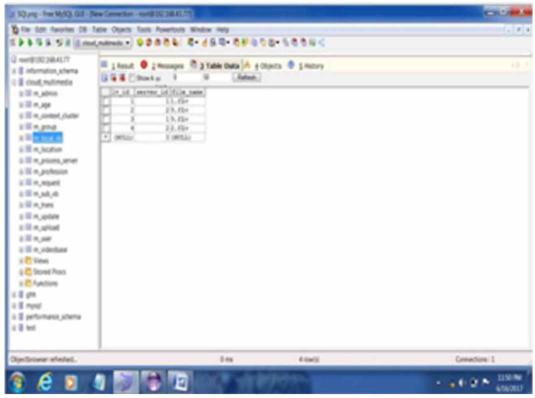


Figure 17. Server used while playing video



clicks on the video that he is interested in, if the service request goes to one of the servers. Since a multi-server system will be able to maintain an enormous number of requests, so they will be placed in a queue. If the server is free the requests are processed quickly or else they are placed in a queue one after another until they are handled by one of the available servers. Here FCFS (first-come-first-serve) queuing is applied.

In addition to the Video recommendation model, a novel geometric differentially private model, which can greatly reduce the performance (recommendation accuracy) loss can be added and Deep learning approaches can be used to build recommendation systems to provide the scale and the consistency in the model. With the fast advancement of Machine Learning, advances in Deep Learning are impressive. Particularly after the RBM training efficiency matter has been settled by the random sample, the unwavering quality of the multi-layer neural network is all the more clearer.

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