

Implementation of Content Based Video Recommendation for Multimedia Big Data

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ABSTRACT: Online social networks have been massively growing multimedia services and offer huge amount of video contents. Because of that users face some problem when they search for particular video. From that huge amount social media user delay in what they want. For that purpose personalized video recommendation system created for the users.

This recommendation system solves the problem user when they search for particular video. But no one has consider both the privacy of user context (e.g. social status, ages, profession and hobbies) and video service providers, which are extremely sensitive and significant in commercial value.

To handle these issues, derive a cloud-assisted differentially private video recommendation system based on distributed online learning. To achieve this, service vendors architecture is modelled as distributed cooperative learners, recommending videos according to users context, with simultaneously adapting the video-selection strategy based on user-click. Here also focus on best accuracy for searching as well recommendation. Vector base cosine similarity (VCS) for score calculation. Each object weight can dene the accuracy against user query of specific video.

The sparsity and heterogeneity of massive social media data may reduce the performance loss of the system. Algorithms outperform existing method and keep delicate balance between computing accuracy and privacy preserved. And also increases efficiency and save time when user search for particular video in social media.

I. INTRODUCTION

In recent years, online social networks (OSNs) have been massively growing, where users can share and consume all kinds of multimedia contents. As a result, given the various s totally different genres of videos in social media, a way to discover the videos of private interest and suggest them to individual l user's area unit of nice significance Recommendation is predicted to be one of the foremost vital services that may offer such personalize multimedia system contents to users. Several l companies have demonstrated initial successes in multimedia recommendation system design. Reported that YouTube won its first Emmy for video recommendations [6]. Actually, most OSNs recommend video content to their users based on the users rich context information (e.g., social status, ages, professions, health conditions and hobbies) contained in their released multimedia data. Regarding this way, several recommendation systems have been proposed. However, there exist two major challenges in this scenario. The first challenge comes from the big data's role in the personalized recommendation. In detail, OSNs have accelerated the reorganization of applications and services, leading to in the explosive increase of social multimedia information. In this case, multimedia big data puts companies in a favorite position to have access to much more contextual information. However, how to harness and actually use big data to effectively personalize recommendation is a monumental task. Traditional stand-alone multimedia systems cannot handle the storage and processing of these large-scale data sets. Besides that, advanced and numerous user-generated multimedia system huge information within the OSNs leads to the sparsity and heterogeneity users context information [1]. Hence, it is extremely challenging to implement recommendation with the multimedia big data. Two difficulties into consideration, establishing a privacy preserving video recommendation system with multimedia bid data can be extremely challenging. Traditionalrecommendersystemsformultimedia,includingcollaborativefiltering(CF) and content-based (CB) recommendation can provide meaningful multimedia recommendations at an individual level[4]. However, their stand-

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alone systems have difficulties in dealing with tremendous high dimensional multimedia big data. As for the privacy concern in recommendation, previously, anonymity was the main tool in recommendation. But the facts that the information can only be partially removed will allow for re-identification. Differential privacy proposed recently is a heuristic method to solve this problem. Informally, differential privacy means that the output is going to be almost exactly the same whether it includes a single user's data in the input datasets. Therefore, hardly can one make an accurate inference on signal users' feature based on the recommendation results. Besides, adding Laplace noise into the recommendation rewards can hide small changes that arise from a single video's contribution. Thus, the revenue gain of one signal video cannot be deduced. Several studies have incorporated it into recommendation systems, but their works only focus on small-scale media data sets, yet executing differential privacy in a large data set often impacts little on accuracy, which works extremely efficiently under the big data context. In conclusion, it is necessary to design a privacy preserving video recommendation that can handle the multimedia big data and achieve high-accurate recommendations. In this paper, we introduce differential privacy into distributed online learning to design an efficient and high-accurate timely recommendation system based on multimedia cloud computing. As illustrated in Fig. 1, user generated multimedia big data (e.g., images, audio clips and videos) is first translated to remote media cloud and stored in decentralized data centers (DCs). Then use technologies such like Bag-of Features Tagging (BoFT) [9][2] to extract users' context vectors and convert the results to distributed video service vendors (servers). Finally recommended video contents are pushed to multimedia applications in OSNs. To goal of each service vendor is to maximize its long term expected total recommendation reward and do not want to reveal their repositories to other service vendors. However, within the cooperation, each service vendor can share some data like the users' context vectors and also the videos' revenue gains with neighbour service vendors. Then, service vendors can infer the repositories of different service vendors from the shared data. To resolve this privacy leak, we tend to adopt Laplace mechanism, adding noise to shared revenue gains. As for the users' privacy, to forestall the exposure of their feature by the recommendation videos, adding noise to the revenue gains isn't non-effective. As a result of the gain is created when the suggested video is revealed and troubling the correct estimation of gains of their own videos with this noise isn't necessary [1]. Thus, we tend to use exponential mechanism to safeguard the users' privacy, wherever the service vendors randomly choose the video according to a computed exponential chance. Featured with the actual fact that users' contexts (d-dimensional purpose within the context area) are distributed over the context space.

II. RELATED WORK

Several recommendation algorithms have been exploited inside the beyond. Content-primarily based filtering (CB) recommendation structures [11]–[12] awareness at the similarities of content material titles, tags and descriptions and they find person-interested objects based on user's man or woman analyzing records. CB recommender structures are easy to installation. Nevertheless, sincerely representing the users' seasoned file information by using a bag of phrases isn't sufficient to capture the exact interests of the consumer. Collaborative filtering (CF) recommendation structures [13], [14] depend on considerable user transaction histories and content material reputation. CF systems require sufficient records consumption document and comments, which isn't suitable to actual-time recommendation. Graph-primarily based (GB) recommendation structures [15], construct a graph to calculate the correlation between recommendation gadgets. Then, recommendation hassle becomes a node selection problem on a graph. Except that, users' co-tagging behaviors and friendships in social network are defined by a graph. Combining graph idea with advice is a marvellous idea. However, in Online Social Networks, this graph can be continuously changeable. Constructing and storing such graph are impractical. Context-conscious advice structures make advice based on the contextual statistics both of gadgets and customers. And has completed a pioneering in this area, but its centralized framework fails to meet the need of huge records environment. Allotted cooperative recommendation framework can set up recommendation well timed under huge facts environment and affords rigorous overall performance guarantees.

As for the private recommendation systems, anonymity changed into the main device. However, in particular for wealthy, high-dimensional huge facts, maximum anonymization techniques seem to cripple the utility of the records. Further, even though anonymized, customers may be re-identification within the presence of colluding adversaries or those with auxiliary records. On the other hand, prior works lay emphasis on cryptography to make the privacy-touchy

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records inaccessible to any outsiders and the server via encryption. but it normally incurs excessive computation and verbal exchange overheads. Differential privateness [11] proposed in latest years has been included into advice by numerous research. McSherry and Mironov display the way to adapt the main algorithms used inside the internetflix Prize opposition to make private-maintaining guidelines. this is generally finished via including noise to the object covariance matrix, to hide small adjustments that get up from a single users contribution.

III. COMPARATIVE ANALYSIS

1. HIMA SAMPATHI RAO¹ , CH RAMESH BABU² “Privacy Preserving Live Content for Cloud Based Video Recommendation with Multimedia Big Data” Proposed Scheme was Propose a cloud-assisted differentially private video recommendation system based on distributed online learning and also propose novel geometric differentially private model, which can greatly reduce the performance (recommendation accuracy) loss. Refereed points are Idea about cloud-assisted differentially private video recommendation system based on distributed online learning.
2. Ming Cheung, James She, ZhanningJieConnection Discovery Using Big Data of User-Shared Images in Social Media was proposed A multimedia big data system that utilizes this observed phenomenon is proposed as an alternative to user- generated tags and social graphs for follower/followee recommendation and gender identification. To the best of our knowledge, this is the first attempt in this field to prove and formulate such a phenomenon for mass user-shared images along with more practical prediction methods. Referred points these findings are useful for information or services recommendations in any social network with intensive image sharing, as well as for other interesting personalization applications, particularly when there is no access to those exclusive user social graphs.
3. Arjmand Samuel, Muhammad I. Sarfraz, *HammadHaseeb*, SalehBasalamah, and ArifGhafoor, “A Frame work for Composition and Enforcement of Privacy-Aware and Context-Driven Authorization Mechanism for Multimedia Big-Data” In this paper, author propose a hybrid approach where privacy requirements square measure captured in an access control system and present a framework for composition and enforcement of privacy policies. The main focus is to permit a user, not a system or security administrator to compose connect free policies for their online multimedia data.
4. F.O. Isinkaye a,, Y.O. Folajimi b, B.A. Ojokoh “ Recommendation systems: Principles, methods and Evaluation” In this paper Author propose different characteristics and potential of different prediction technique in recommendation system. It will solve the problem of information overload and this traditional technique and their strength and challenges improve the performance of system
5. M. Tkalcic, A. Odic and A. Kosir“Affective labeling in a content-based recommender system for images” In this paper author present a methodology for the implicit acquisition of emotional labels for pictures. It’s supported an emotion detection technique that takes as input the video sequences of the users facial expressions.

IV. SYSTEM ARCHITECTURE

A novel geometric differentially private method to promote the total reward. We propose a media based video recommendation system and rigorously formulate it as a distributed online learning problem. In our model, decentralized service vendors work cooperatively to deal with large scale contextual data. To handle the dimensionality and sparsity of the multimedia big data, our method adaptively partitions the context space for each service vendor. Evaluation results show this method has lower performance loss and converges fast to optimal strategy. To the best of our knowledge, we are the first to deal with the privacy issue of both the social media users and video service vendors in recommendation.

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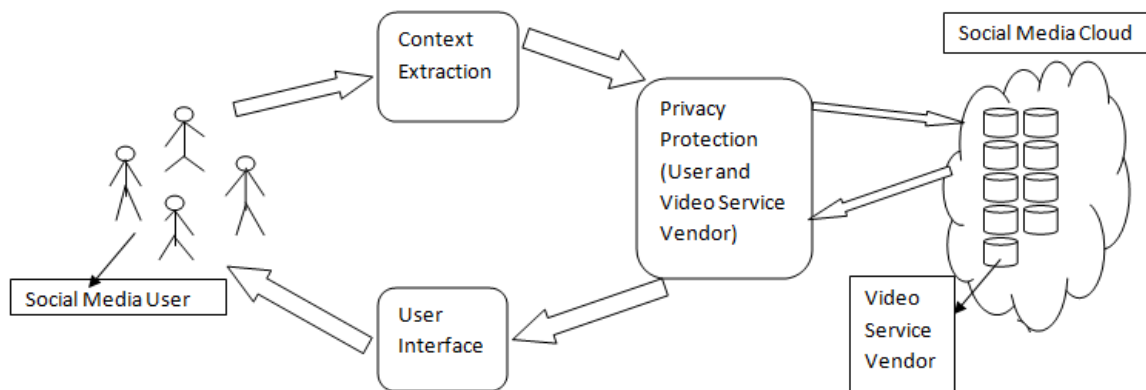


Fig.1. Multimedia cloud based video recommendation system

We guarantee ϵ -differential privacy while not coming at substantial expense in total reward. Here use vector base cosine similarity for score calculation which provide bset accuracy for searching as well as recommendation.

V. ALGORITHMS USED

Weight calculation Algorithm

Input: Query generated from user Q, each retrieved list L from webpage.

Output: Each list with weight.

Here system have to find similarity of two lists: $a = (a_1, a_2, a_3, \dots)$ and $b = (b_1, b_2, \dots)$, where a_n and b_n are the components of the vector (features of the document, or values for each word of the comment) and the n is the dimension of the vectors:

Step 1: Read each row R from Data List L

Step 2: for each (Column c from R)

Step 3: Apply formula (1) on c and Q

Step 4: Score=Calc(c,Q)

Step 5: calculate relevancy score for attribute list.

Step 6: assign each Row to current weight

Step 7: Categorize all instances

Step 8: end for end procedure

VI. EFFICIENCY CALCULATION WITH EXISTING SYSTEM

In the existing system used TF-IDF for score calculation and proposed used the Vector base Cosine Similarity (VCS) algorithm. The Table 1 shows the efficient between proposed and existing algorithm.

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Table 1: Time required in seconds for TF-IDF and VCS for listed weight calculation

Algorithm	10 List	20 List	30 List
TF-IDF	154	312	457
VCS	139	277	401

The overall outcome of system is better than existing portal base search engines; it can achieve automated search as well as privacy into the system. The accuracy of system also better than other privacy base search engines. The system has already connect with cloud so, it can available 24*7 to end user over the internet.

VII. EXPERIMENTAL SETUP

To analyse and study the performance of video recommendation system we have to evaluate some experimental setup. The system is built using Java framework (version jdk 7.1 or higher) on Ubuntu as well as Windows platform. The Eclipse(MARS 2) is used as a development tool. The system doesn't require any specific hardware to run; any standard machine is capable of running the application.

VIII. RESULTS AND DISCUSSIN

a. Datasets

Multimedia datasets: Video dataset. All the video files dataset which id downloaded from Youtube API and process for recommendation.

b. Results

In this paper we find the best video recommendation to the particular user. In existing system, recommendation is based on user feedback. In proposed, recommendation is done by VCS which provide weight calculation for particular video. And also provide best accuracy search, security and recommendation. It also saves time of user searching.

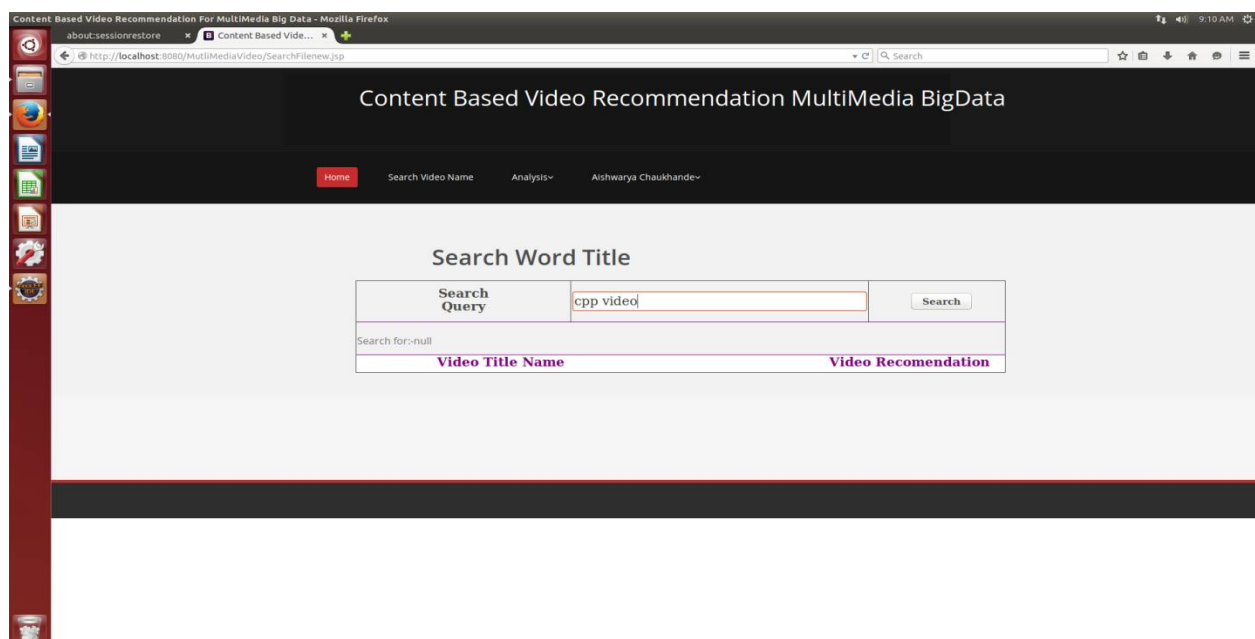


Fig 2: user search a text query

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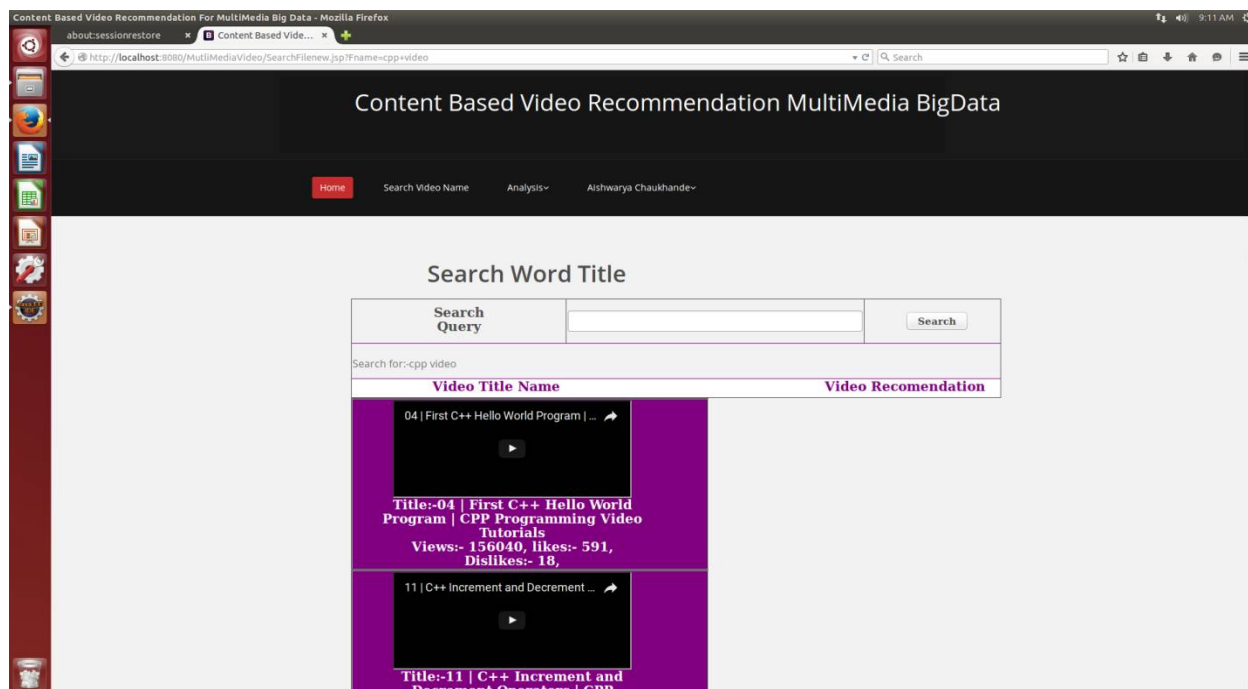


Fig 3: Recommended videos for user

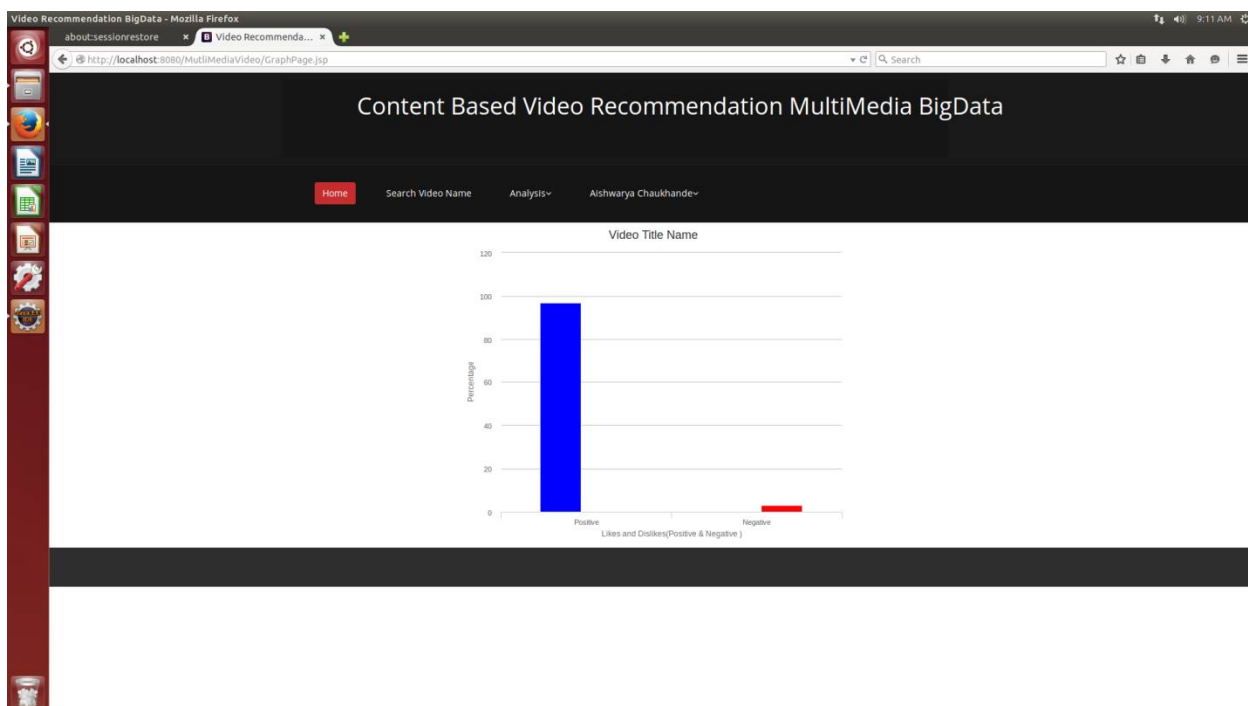


Fig 4: Positive/ Negative comment Analysis Graph

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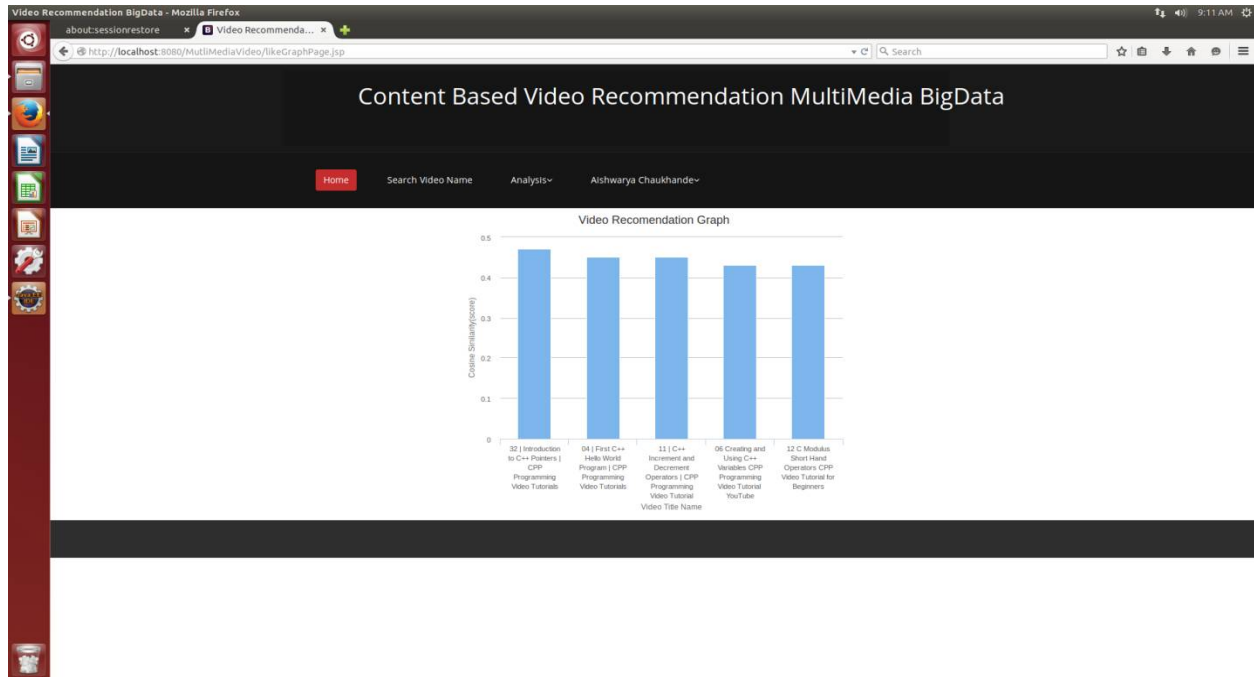


Fig 5: Vector Cosine Similarity Video Recommendation Graph

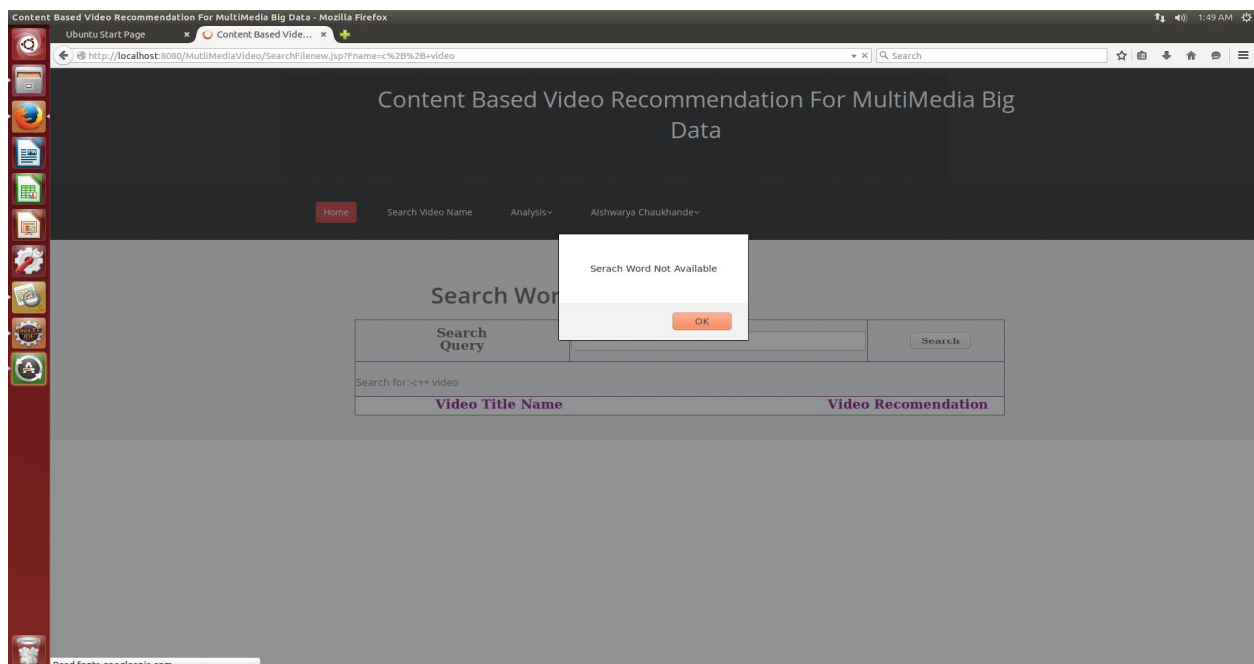


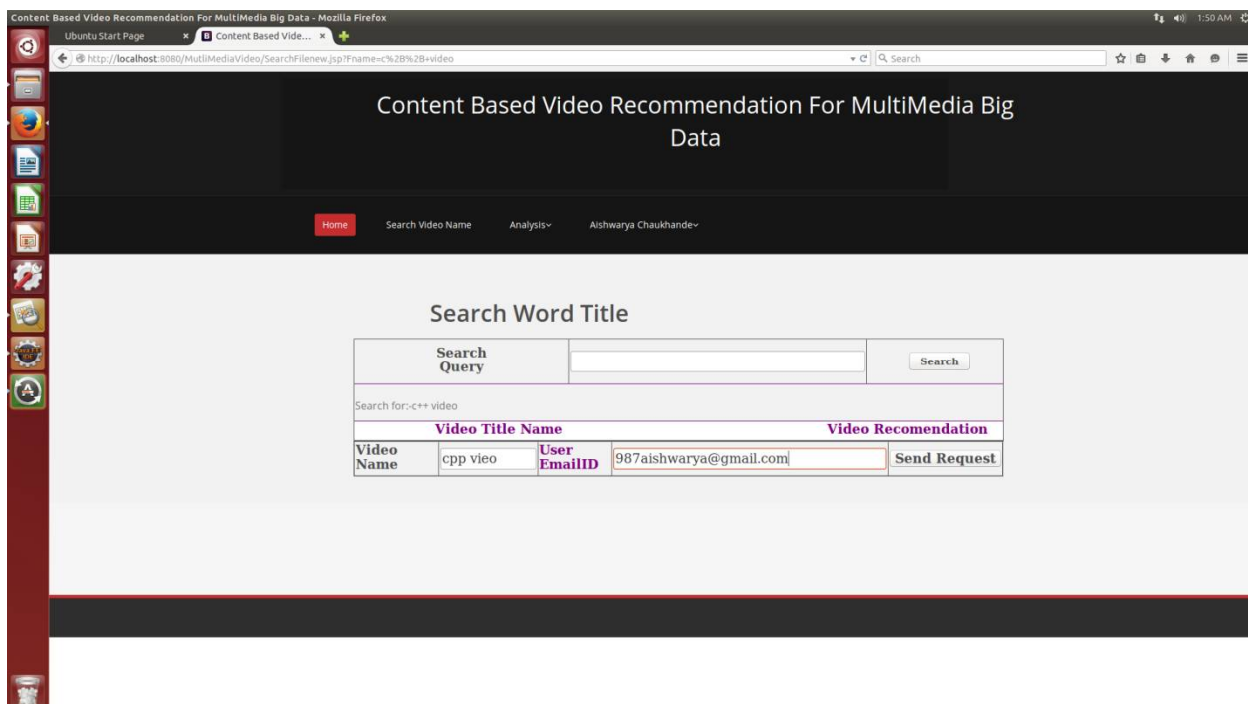
Fig 6: Video not found in database

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Home Search Video Name Analysis Aishwarya Chaukhande

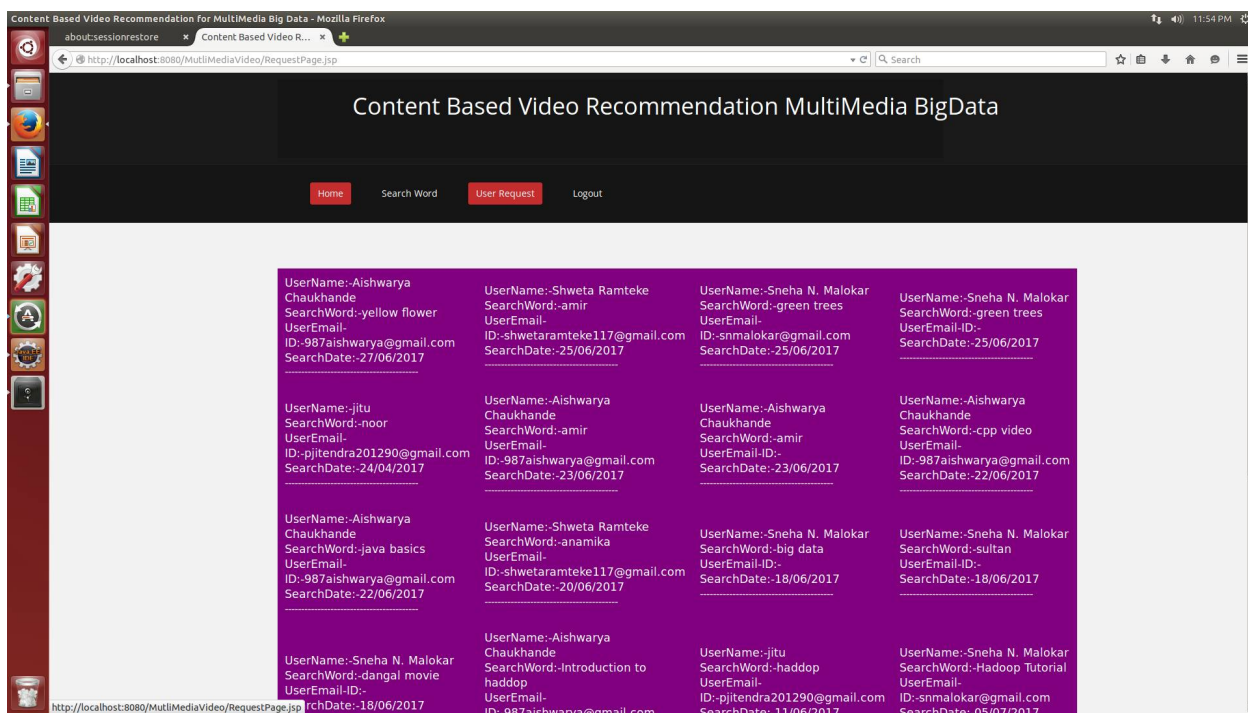
Search Word Title

Search Query Search

Search for: c++ video

Video Title Name	Video Recommendation
Video Name cpp vleo	User EmailID 987aishwarya@gmail.com Send Request

Fig 7: send request to admin



Content Based Video Recommendation MultiMedia BigData

Home Search Word User Request Logout

UserName: Aishwarya Chaukhande SearchWord: yellow flower UserEmail: 987aishwarya@gmail.com SearchDate: 27/06/2017	UserName: Shweta Ramteke SearchWord: amir UserEmail: shwetaramteke117@gmail.com SearchDate: 25/06/2017	UserName: Sneha N. Malokar SearchWord: green trees UserEmail: snmalokar@gmail.com SearchDate: 25/06/2017	UserName: Sneha N. Malokar SearchWord: green trees UserEmail: snmalokar@gmail.com SearchDate: 25/06/2017
UserName: jitu SearchWord: noor UserEmail: pjitendra201290@gmail.com SearchDate: 24/04/2017	UserName: Aishwarya Chaukhande SearchWord: amir UserEmail: 987aishwarya@gmail.com SearchDate: 23/06/2017	UserName: Aishwarya Chaukhande SearchWord: amir UserEmail: 987aishwarya@gmail.com SearchDate: 23/06/2017	UserName: Aishwarya Chaukhande SearchWord: cpp video UserEmail: 987aishwarya@gmail.com SearchDate: 22/06/2017
UserName: Aishwarya Chaukhande SearchWord: java basics UserEmail: 987aishwarya@gmail.com SearchDate: 22/06/2017	UserName: Shweta Ramteke SearchWord: anamika UserEmail: shwetaramteke117@gmail.com SearchDate: 20/06/2017	UserName: Sneha N. Malokar SearchWord: big data UserEmail: snmalokar@gmail.com SearchDate: 18/06/2017	UserName: Sneha N. Malokar SearchWord: sultan UserEmail: snmalokar@gmail.com SearchDate: 18/06/2017
UserName: Sneha N. Malokar SearchWord: dangal movie UserEmail: snmalokar@gmail.com SearchDate: 18/06/2017	UserName: Aishwarya Chaukhande SearchWord: Introduction to hadoop UserEmail: 987aishwarya@gmail.com SearchDate: 18/06/2017	UserName: jitu SearchWord: hadoop UserEmail: pjitendra201290@gmail.com SearchDate: 11/06/2017	UserName: Sneha N. Malokar SearchWord: Hadoop Tutorial UserEmail: snmalokar@gmail.com SearchDate: 05/07/2017

Fig 8: Request Page for admin

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IX. CONCLUSION

In the multimedia system manage large volume of data and heterogeneity of big data. To tackle with the large value and heterogeneity of big data, we adopt dynamic space partition to distributed contextual bandit. PDAP algorithm gives efficient video recommendation in social network by using user clicks. Algorithm PDAP, Provide privacy of social network user and video service vendor. For that purpose ExP-DAP and LaP-DAP Algorithm use. By using this algorithm the performance loss and privacy preserving expected to achieve. Vector cosine similarity (VCS) for score calculation not only provides best accuracy for searching but also it provides best recommendation to the user.

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