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Online Video Promotion with User Specific Information

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ABSTRACT: There are various ways and methods used in video recommendation which are purely statistical. These would give recommendations to users based on either their previous search or other criteria. These systems set up a large number of context collectors at the terminals. However, the context collecting and exchanging result in heavy network overhead, and the context processing consumes huge computation. Due to these criterion users end up getting unnecessary content which makes the browser slow. In this paper we propose a user specific category based promotion, we propose and provide for characterization of individual content as well as social attributes that help distinguish each user class. Thus a user defined video recommendation would ensure faster access to only important information which is in the user's domain of interest which utilises low buffer space and increase the speed of the system for user satisfaction.

KEYWORDS: Spammer ,User created content, Video-Tag , private storage, recommender.

I.INTRODUCTION

Online video sharing systems, out of which YouTube[1] is the most popular, provide features that allow users to post a video as a response to a discussion topic. These features open opportunities for users to introduce polluted content, or simply pollution, into the system. So we find For instance, spammers[2] may post an unrelated video as response to a popular one, their objective being to increase the viewer-ship of their content. According to Cisco forecast[3] by 2015, two-thirds of the world's mobile data traffic and 62% of the consumer Internet traffic will be video. Video sharing has continuously increased ground due to advancement in network bandwidth[4] that now manage to relay such content across the internet faster as well as maintaining the quality.

Internet users post a large number of video clips on Video-sharing websites and social network applications[5] every day. The video content may be duplicate, similar, related, or quite different. Facing billions of multimedia WebPages, online users are usually having a hard time finding their favourites. Some video-sharing websites recommend video lists for end users according to video classification, video description tags, or watching history. However, these recommendations are not accurate and are always not consistent with the end users' interests. To improve this, some websites also provide users with search engine[6] to search their desired videos quickly.

This led to the development of personalization methods which collect and analyse the viewing patterns, such as: the target user's viewing pattern for contents, statistical information for the overall user's viewing patterns, a user's private profile or preference information through the analysis of a user's computing environment, a communication service, and the preferred device types such as a mobile phone, personal computer, etc. A content-based recommendations system recommends the most likely matched item, then compares the recommendation list to a user's previous input data or compared to preference items. It is also based on information searching and generally uses a rating method which is used in the information searching. The rating method calculates a user's preference information and items in a recommendation list. It recommends the most likely program in a user's profile.

This method has the advantage with easily adopt in recommendation result and enable more quickly recommendation. But it has problems with difference result and efficient refer to appropriate rating configuration.

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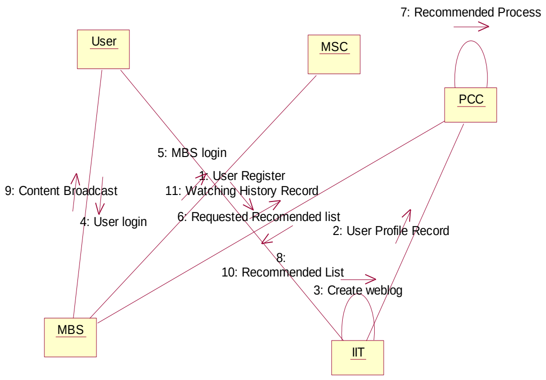

Fig 1 Collaboration diagram

In use there are several video recommendation algorithms that have been developed; these would include content-based filtering (CB) by Google[7]. This has adopted for their recommender system in AdWords services. It returns search results with keyword-related advertisements, like spam these advertisements annoy most users and have been ignored by most users. Also included are social network filtering (SNF)[8] which is used by Facebook.

In Internet User Created Contents (UCC), and Online Digital Video (ODV) enabled the rapid increase of online Video and programs which can be selected by consumers. This was not expected when we consider the conventional Video technologies and policies. Due to these paradigm changes, thousand of video and programs are now available to consumers. In the existing limited content providers existed, such as licensed broadcasting companies and a small number of video and satellite broadcasting operators. Thus the number of movie and programs were limited. It has become difficult and time consuming to find an interesting movie video and program via the remote control or channel guide map.
In this paper we propose a user defined recommendation system(UDC) under a cloud computing environment. The proposed UDV system analyses and uses the viewing pattern of consumers to personalize the program recommendations, and to efficiently use computing resources. A proposed framework for recommending online videos operates by constructing user profiles as an aggregate of tag clouds and generating recommendations according to similar viewing patterns.
The proposed personalization method collects and analyses the viewing patterns, such as : the target user's viewing pattern for contents, statistical information for the overall user's viewing patterns, a user's private profile or preference information through the analysis of a user's computing environment, a communication service, and implemented in personal computer, but in future we preferred the Mobile device .

II. RELATED WORK

It considers a network with N mobile unlicensed nodes that move in an environment according to some stochastic mobility models. It also assumes that entire spectrum is divided into number of M non-overlapping orthogonal channels having different bandwidth. The access to each licensed channel is regulated by fixed duration time slots. Slot timing is assumed to be broadcast by the primary system. Before transmitting its message, each transmitter node, which is a node with the message, first selects a path node and a frequency channel to copy the message. After the path and channel selection, the transmitter node negotiates and handshakes with its path node and declares the selected channel frequency to the path. The communication needed for this coordination is assumed to be accomplished by a fixed length frequency hopping sequence (FHS) that is composed of K distinct licensed channels. In each time slot, each node consecutively hops on FHS within a given order to transmit and receive a coordination packet. The aim of coordination packet that is generated by a node with message is to inform its path about the frequency channel decided for the message copying.

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In 2005 Gediminas Adomavicius and Alexander Tuzhilin in their paper Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions[9], they present an overview of the field of recommender systems and describe the current generation of recommendation methods that are classified as:

1. content-based,
2. collaborative, and
3. hybrid recommendation

They went further to describe some shortcomings of present recommendation systems and also proposed possible extensions that can improve recommendation capabilities and make recommender systems applicable to an even broader range of applications. These extensions include an improvement of understanding of users and items, incorporation of the contextual information into the recommendation process, support for multi-criteria ratings, and a provision of more flexible and less intrusive types of recommendations.

Daisuke Yamamoto, Tomoki Masuda, Shigeki Ohira, and Katashi Nagao of Nagoya University in their article - Video Scene Annotation Based on Web Social Activities of 2008 [10]. They describes a mechanism to acquire the semantics of video content from the activities of Web communities that use a bulletin-board system and weblog tools to discuss video scenes. However they proposed extraction of more semantic information by use of ontology to scene tags or using an advanced language analysis. They also proposed a construct semantic hypermedia networks based on quotations from video scenes.

Visualizing Tags over Time, a paper written by Micah Dubinko et al [12] in 2007 considers the problem of visualizing the evolution of tags within the Flickr online image sharing community. Users of the Flickr service can append a tag to a photo in the system. Understanding the evolution of these tags over time is therefore a challenging task so they proposed an approach based on a characterization of the most interesting tags associated with a sliding interval of time.
Yijun Mo, Jianwen Chen, Xia Xie, Changqing Luo, and Laurence Tianruo Yang,[11] proposed a cloud-based mobile multimedia recommendation system which can reduce network overhead and speed up the recommendation process is proposed. The users are classified into several groups according to their context types and values. With the accurate classification rules, the context details are not necessary to compute, and the huge network overhead is reduced. moreover, user contexts, user relationships, and user profiles are collected from video-sharing websites to generate multimedia recommendation rules based on the Hadoop platform. When a new user request arrives, the rules will be extended and optimized to make real-time recommendation. The results show that the proposed approach can recommend desired services with high precision, high recall, and low response delay.

III.USER DEFINED VIDEO RECOMMENDATION

Personalization makes it quick and easy to dynamically find a video based on a user's preference in the number of video, and enables easy access. For this personalization a recommendation system is necessary. In Internet User Created Contents (UCC)[13], and Online Digital Video (ODV)[14] enabled the rapid increase of online Video and programs which can be selected by consumers. This was not expected when we consider the conventional Video technologies and policies. Due to these paradigm changes, thousand of video and programs are now available to consumers. In the existing limited content providers existed, such as licensed broadcasting companies and a small number of video and satellite broadcasting operators. Thus the number of movie and programs were limited. It has become difficult and time consuming to find an interesting movie video and program via the remote control or channel guide map. To refine the channel selecting processes and to satisfy the consumer's requirements, we propose the Online Video Recommendation (ODV) system under a cloud computing environment. The proposed ODV system analyses and uses the viewing pattern of consumers to personalize the program recommendations, and to efficiently use computing resources. A proposed framework for recommending online videos operates by constructing user profiles as an aggregate of tag clouds and generating recommendations according to similar viewing patterns.

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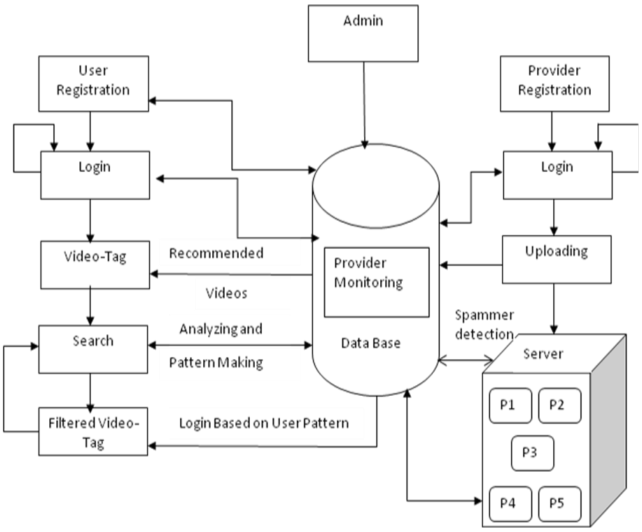

Fig 2. Architectural design

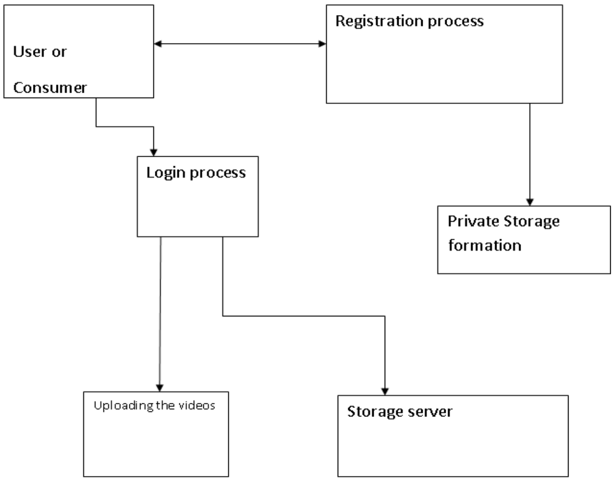

Fig 3. Private storage formation

The proposed personalization method collects and analyses the viewing patterns, such as : the target user's viewing pattern for contents, statistical information for the overall user's viewing patterns, a user's private profile or preference information through the analysis of a user's computing environment, a communication service, and implemented in personal computer, but in future we preferred the Mobile device .

A. ARCHITECTURE

From architecture specific Video-Tag will be added to every user, Here Video-Tag is the type or category of videos which the user likes, such as Movies , News and Sports etc. As the user signs up, they have to choose the category of videos they would want recommended on their login. The administrator provides separate storage space for every video provider in database. Providers will specify the video tag for every video they provide while they are uploading. The video classification will be done during the uploading of every single video by assigning video tag. When the user logins into the system based on the user Video-Tag videos are automatically advertised on the user's home page.

Spammers will be identified based on the counter value; Counter value is incremented by every dislike for video. if any user dislikes particular video that video will disappear from that users recommendation list, likewise the more users dislikes the same provider's videos that video provider will be specified as spammer using the count number of users dislikes. Once the provider specified as spammer that provider will not get access to the system and providers space will be removed from storage until they verify with the administrator.

B .PRIVATE STORAGE FORMATION

We make a Private Storage Space for every Provider in our media storage Server. At the time of creating a Provider account the video storage space will be allocated to the provider. That memory of the storage space is not a fixed, it can large-scale storage .From this format we can uphold videos confidentially.

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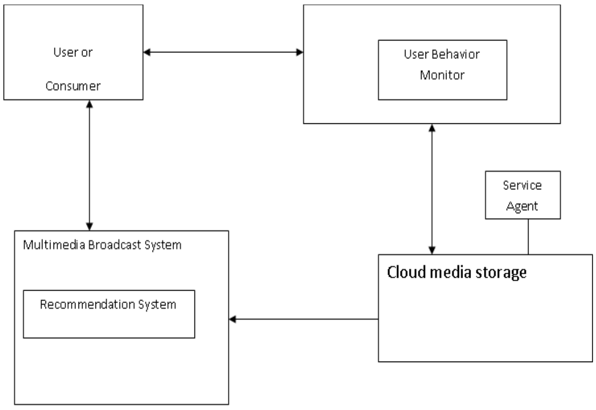

Fig 4 user recommender system

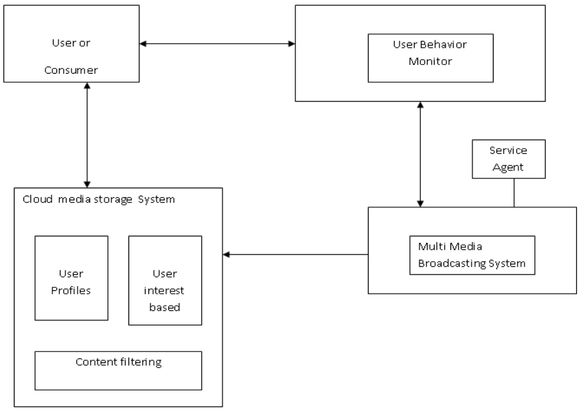

Fig 5. Content filtering and reusability

The Private Storage Formation (PSF) monitors the target consumer's personal profile. The PSF supports management, scheduling, security, privacy control of the consumer profile, and the required resources. In the proposed system, each intelligent device individually transfers weblog history to the PSF. The Profile Manager (PM) then analyses the combined weblog, and creates the consumer profile based on this weblog. The proposed PSF can identify the consumer's preference in a short amount of time, and provide a recommended channel list at initial time. Tags can be aggregated in various ways to characterize an entity of User interest. tag information is referred to as a tag, which is usually displayed in alphabetical order and visually weighted by font size. The PSF is also independent of the device location, and can provide consistent profile information according to the consumer for various devices.

Storage Formation gives developers and systems administrators an easy way to create and manage a collection of related AWS resources, provisioning and updating them in an orderly and predictable fashion.
You can use AWS Formation's sample templates or create your own templates to describe the AWS resources, and any associated dependencies or runtime parameters, required to run your application. You don't need to figure out the order in which AWS services need to be provisioned or the subtleties of how to make those dependencies work. Private storage Formation takes care of this for you. Once deployed, you can modify and update the AWS resources in a controlled and predictable way allowing you to version control your AWS infrastructure in the same way as you version control your software.

You can deploy and update a template and its associated collection of resources (called a stack) via the AWS Management Console, storage Formation command line tools or APIs. storage Formation is available at no additional charge, and you pay only for the AWS resources needed to run your applications.

C. USER RECOMMENDER SYSTEM

A content-based recommendations system recommends the most likely matched item, then compares the recommendation list to a user's previous input data or compared to preference items. A content-based recommendations system is based on information searching and generally uses a rating method which is used in the information searching. To measures for computing the user similarity, namely tag cloud-based cosine (TCC)[15] and tag cloud similarity rank (TCSR). The Profile Filtering Agent (PFA)[16] creates a personalized channel profile based on the accumulated viewed content list by using a content based filtering.

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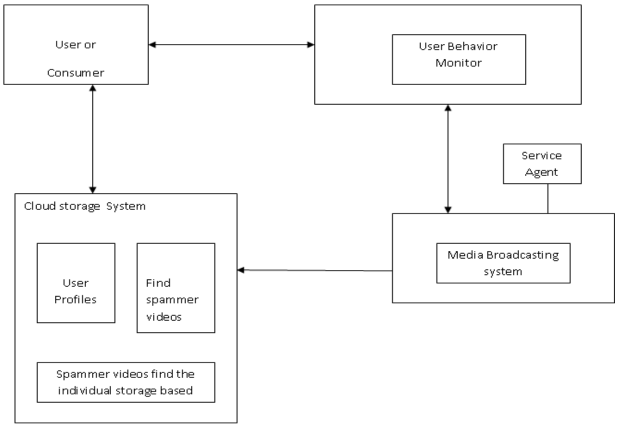

Fig 6 spammer detection

Users can Recommend the videos to the user itself, at the time of user profile creation. The Recommended videos post to the client profile as video tag system. The video tag is generated based on the user Recommended. Recommender systems or recommendation systems (sometimes replacing "system" with a synonym such as platform or engine) are a subclass of information filtering system that seek to predict the 'rating' or 'preference' that a user would give to an item (such as music, books, or movies) or social element (e.g. people or groups) they had not yet considered, using a model built from the characteristics of an item (content-based approaches) or the user's social environment (collaborative filtering approaches). Recommender systems have become extremely common in recent years.

When viewing a product on Amazon.com, the store will recommend additional items based on a matrix of what other shoppers bought along with the currently selected item. Pandora Radio takes an initial input of a song or musician and plays music with similar characteristics (based on a series of keywords attributed to the inputted artist or piece of music). The stations created by Pandora can be refined through user feedback (emphasizing or deemphasizing certain characteristics).Netflix offers predictions of movies that a user might like to watch based on the user's previous ratings and watching habits (as compared to the behaviour of other users), also taking into account the characteristics (such as the genre) of the film.

D. CONTENT FILTERING AND REUSABILITY

A content-based recommendations system recommends the most likely matched item. To compares the recommendation list to a user's previous input data or compared to preference items. A content-based recommendations system is based on information searching and generally uses a rating method which is used in the information searching. The Profile Filtering Agent (PFA) creates a personalized channel profile based on the accumulated viewed content list by using a content based filtering. On the Internet, content filtering (also known as information filtering) is the use of a program to screen and exclude from access or availability Web pages. Content filtering is used by corporations as part of Internet firewall computers and also by home computer owners, especially by parents to screen the content their children have access to from a computer.

Content filtering usually works by specifying character strings that, if matched, indicate undesirable content that is to be screened out. Content is typically screened for pornographic content and sometimes also for violence- or hate-oriented content. Critics of content filtering programs point out that it is not difficult to unintentionally exclude desirable content. Content filtering and the products that offer this service can be divided into Web filtering, the screening of Web sites or pages, and video filtering, the screening of video for spam or other objectionable content. A Web filter[17] is a program that can screen an incoming Web page to determine whether some or all of it should

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not be displayed to the user. The filter checks the origin or content of a Web page against a set of rules provided by company or person who has installed the Web filter.

E. SPAMMER DETECTIONS

Spammers may post an unrelated video as response to a popular one. We detect the spammers using customer suggestion private storage formation process. Also lazy associative classification algorithms can be used to automatically detect spammers then classifying them as spammers, promoters, and legitimate users. Using our test collection, we provide a characterization of content, individual, and social attributes that help distinguish each user class. The researchers then investigate the feasibility of using supervised classification algorithms to automatically detect spammers and promoters, and assess their effectiveness in our test collection. The researchers achieved this by analysing a variety of video, individual and social attributes that reflect the behaviour of our sampled users, aiming at drawing some insights into their relative discriminatory power in distinguishing legitimate users, promoters, and spammers. Fourth, using the same set of attributes, which are based on the user's profile, the user's social behaviour in the system, and the videos posted by the user as well as her target (responded) videos, we investigated the feasibility of applying supervised learning methods for identifying the two envisioned types of polluters. We consider two state-of-the-art supervised classification algorithms, namely, support vector machines (SVMs)[18] and lazy associative classification (LAC)[19]. We evaluated both algorithms over our test collection, finding that both techniques can effectively identify the majority of the promoters and spammers.

IV.EXPERIMENTAL ANALYSIS AND RESULTS

We provide a characterization of content, individual, and social attributes that help distinguish each user class. Our classification approach succeeds at separating spammers and promoters from legitimate users; the high cost of manually labelling vast amounts of examples compromises its full potential in realistic scenarios.

By implementing Spammers we will restrict the irrelevant content videos for users and provides the content which user wants. User personalization makes it quick and easy to dynamically find a video based on a user's preference in the number of videos, and enables easy and faster access. The Table bellow shows that Categorization of users based on their favourite video recommendations .

No	User Name	Password	Mail Address	Favourite
1	Prabas	Abc&123	prabas@gmail.com	Movies
2	Mahesh	Bcd#234	mahesh@gmail.com	News
3	Pawan	Cde$345	pa1@gmail.com	Songs
4	Ravitej	Def%456	ravi@gmail.com	Sports

Table1.Users DataBase

V.CONCLUSION

In this paper, we have proposed a user based recommender system for videos. This is where users specify their categories of interest thus recommendations would be channelled accordingly. However if a spammer achieves to penetrate users, by disliking a video, would be voting for it to be a spam thus it would be blocked. Yes systems through statistical means can detect spam but human users can do it better.

In future a strong combination of user contribution and statistical methods especially use of big data analytics would go a long way in shielding users from annoying video recommendations from spammers

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