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Video Promotion on Multi Platform Network

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***Abstract*— In some social video networking sites such as YouTube, there exists large numbers of duplicate video in the database. Inorder to open the video and find whether they are duplicate it is very difficult for the users. If a user is having limited usage of internet connectivity, it will be a waste of cost as well as time to view the duplicate videos. Social media sites such as Facebook, Twitter like have greater influence on video promotion. The rapid growth of video content on the internet and its corresponding storage cost has recently drawn much attention to the task of video duplication. The proliferation of duplicate videos could impact many aspects of data centre and network operations and, as a result, have negative effects on the user experience. From the video server's point of view, duplicate videos could increase power, data storage, and therefore overall costs of data centre operations. Large number of duplicate videos will impact network performances, storage, cost etc. So we have to avoid duplicate video contents from social media sites that uploaded and shared, retweet by users. The problem is how to improve video dissemination by avoiding duplicate videos. The proposed framework also enables solutions for these problems. From cross network association actually obtain the association between YouTube video interests and Twitter following patterns.**

***Index Terms*— video promotion, multi-platform network, social media, video to frame converter**

I. INTRODUCTION

The emergence and rapid proliferation of various social media networks have reshaped the way how video contents are generated, distributed and consumed in traditional video sharing portals. Nowadays, online videos can be accessed from far beyond the internal mechanisms of the video sharing portals, such as internal search and front page highlight. Recent studies have found that external referrers, such as external search engines and other social media websites arise to be the new and important portals to lead users to online videos.To establish a reasonable cross-network association between social media websites .i.e. the fact that the same individual usually involves with different social media networks and different social media networks share Remarkable percentage of overlapped users. If we know different users who show interest to a given video (e.g., upload, favourite, add to playlist), it is confident to identify the video that will be already uploaded by the same person in different social media networks and it will reduce the memory consumption. Therefore, introducing a brand new way to establish the cross-network association by leveraging the collective intelligence of the observed overlapped users.The aim of the paper is to create a cross network association for identifying the overlapped users. Identify all the videos in a social media network and there by avoid duplication in a video content. In some social video networking sites such as YouTube, there exists large numbers of duplicate video in the database. If a user is having limited usage of internet connectivity, it will be a waste of cost as well as time to view the duplicate videos. External referrals such as Facebook, Twitter [1] like social media sites have greater influence on video promotion. The rapid growth of video content on the Internet and its corresponding storage cost has recently drawn much attention to the task of video duplication. Followers to these users then receive the tweet feed and become the potential viewers of these videos. Under this followee-follower structure, Twitter followees, especially those with a lot of followers (which we refer to as popular followee), play important roles under social media circumstances by: (1) acting as we media, via the control of Information dissemination channels to millions of audiences, and (2) acting as influential leaders, via their potential impact on the followers decisions and activities. [5] proposed a system in which the cross-diamond search algorithm employs two diamond search patterns (a large and small) and a halfway-stop technique. It finds small motion vectors with fewer search points than the DS algorithm while maintaining similar or even better search quality. The efficient Three Step Search (E3SS) algorithm requires less computation and performs better in terms of PSNR. Modified objected block-base vector search algorithm (MOBS) fully utilizes the correlations existing in motion vectors to reduce the computations. Fast Objected - Base Efficient (FOBE) Three Step Search

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algorithm combines E3SS and MOBS. By combining these two existing algorithms CDS and MOBS, a new algorithm is proposed with reduced computational complexity without degradation in quality.

YouTube video Gangnam Style went viral to become thirst web video that reaches one billion views in 5 months, resulting mainly from its successful strategy of roping in some popularly followed musicians on Twitter, such as Britney Spears, Justin Bieber and Katy Perry. In this1 Effective Video Promotion on Cross-Platform networks context, if we can identify proper followees to help disseminate videos, their significant audience accessibility and behavioural impact will guarantee the promotion efficiency. Therefore, the problem of this work is: For specific YouTube video, to identify proper Twitter followees with goal to maximize video dissemination to the followers .But there will be more chance of increase in duplicate level of video contents. Further, duplicate videos have the potential to harm caching systems, degrading cache efficiency by taking up space that could be used for unique Content and increasing the amount of data that must be sent over the network to in-network caching systems. These inefficiencies could be passed onto the user in the form of duplicated search results, longer startup delays, and interrupted streaming Hence in this project, to balance the speed and accuracy aspects, combine the contextual information such as time duration, number of views and content information such as color and local points to achieve real-time duplicate video elimination. Here going to select a group of similar videos as dominant group based on time duration and select a seed video from the dominant group. The videos are segmented [7] into frames in the form of JPEG images and the frames of the seed video are compared with the frames of the other videos. The duplicate videos are thus eliminated from the database. The videos used are in the MP4 format. Here create a model social video networking site and use some of the videos present in the database to illustrate the example for duplicate video elimination using content information and context information. To the best of our knowledge, this is the first attempt to mine the multi-network association under a user-bridged scheme. After the related studies in Section II, proposed methodology is discussed in Section III . Section III consists of user registration module, cross platform module, video uploading module, memory management module ie; first upload the videos into different cross plaform. Video are uploaded to these different platforms through the Video Uploading Module we can upload either same or different videos. Next we use a FFMPEG software library that is used to manipulate videos .Each uploaded video is then converted into frame using a video to frame converter here we use FFMEG software library Then in memory management module or in sample matching algorithm we use a pixel based matching algorithm for mathching each videoframes and to avoid the duplication of videos. Here the works as follows: find the width and height of each frames is compared and also the RGB component. *In* Section IV, the conclusion summarizes the paper.

II. RELATED STUDIES

This section reviews the related topics. Instead of a complete coverage, we only review the representative works in each topic, with the goal to position this work in the coordinate of existing works for better understanding the addressed problem and the proposed solution. With various social media networks growing in prominence, netizens are using a multitude of social media services for social connection and information sharing. Cross-network collaborative applications have recently attracted attentions. One line is on cross-network user modeling, which focuses on integrating various social media activities. In [1], the authors introduced a cold-start recommendation problem by aggregating user profiles in Flickr, Twitter and Delicious. Deng et al. has proposed a personalized YouTube video recommendation solution by incorporating user information from Twitter [10]. Another line is devoted to taking advantage of different social networks' characteristics towards collaborative applications. For example, Suman et al. exploited the real-time and socialized characteristics of the Twitter tweets to facilitate video applications in YouTube [30]. In [26], Twitter event detection is conducted by employing Wikipedia pages as the authoritative references. Our work belongs to the second line, where a collaborative application is designed to exploit the propagation efficiency of Twitter to meet the YouTube video promotion demand. As mentioned byFabian Abel, Samur Araújo , Qi Gao, Geert-Jan Houben "Analyzing cross-system user modeling on the social web," analyze tag-based user profiles, which result from social tagging activities in Social Web systems and particularly in Flickr, Twitter and Delicious. Investigate the characteristics of tag-based user profiles within these systems, examine to what extent tag-based profiles of individual users overlap between the systems and identify significant benefits of cross-system user modeling by means of aggregating the different profiles of a same user.

Presenting a set of cross-system user modeling strategies and evaluate their performance in generating valuable profiles in the context of tag and resource recommendations in Flickr, Twitter and Delicious. The evaluation shows that the cross-system user modeling strategies outperform other strategies significantly and have tremendous impact on the recommendation quality in cold-start settings where systems have sparse information about their users As mentioned by S. Bhagat, Anyone who has watched videos on YouTube, or any other video sharing service, has certainly noticed that near-duplicates of the same video often appear in the search results or are recommended as related videos. These impressions, however, are not useful toward making recommendations for taking action to mitigate any potential efficiency loss resulting from unnecessary duplication. Duplicate ratio content is more in existing systems. Viewing a small number of individual search results, however, is unlikely to yield good estimates of the prevalence of duplicates across a video sharing services entire database.

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The huge number of videos stored within services such as YouTube also indicates that manually comparing videos to estimate duplicate ratio is infeasible. This intractability motivates the need for a larger scale assessment, assist in determining the necessity of and formulating further systems to conduct video deduplication.

III. PROPOSED METHODOLOGY

In this section proposed system is explained The key lies in how to establish a reasonable multi-network association between different platform. The proposed system is to identify duplicate videos in a cross network association. And unique videos only stored in the database. Here make 3 social media sites called website1 , website 2 , website 3.A video to frame converter converts videos into images and then by using Edge value, Mean value Computation the duplicate ratio should be identify. Matched videos not allowed store in common data store again. The proposed framework also enables solutions to other applications. From cross network association actually obtain the association between YouTube video interests and Twitter following patterns. Based on this association, cross network personalized recommendation problems on two directions can be enabled: recommending Twitter followee topic or Twitter lists given YouTube video interest, and recommending YouTube videos given Twitter followee list. Moreover, for LA-based solutions, a careful investigation into the derived latent attributes, e.g., checking the coupled factors distribution in the two topic distribution, will gain understanding into the examined user collection and facilitate cross-network collaborative applications like user clustering. User classification can also be conducted if we annotate the derived user attributes. Another promising application is on examining the value of Twitter followees. Current methods value Twitter followees by directly analyzing their followers demographics information, e.g., the followee has a lot of young female followers. The proposed framework in this work facilitates application-oriented Twitter followee value analysis, by associating Twitter followee topic space with the needed topic spaces. For example, this work can be viewed as valuing Twitter followee w.r.t. promotion efficiency to YouTube videos. This significantly expands understanding into the value of Twitter followees. Video promotion by avoiding duplicate videos in cross-networks. The general framework of the proposed scheme consists of following stages: Video uploading to Cross-network, Video to frame conversion, Frame comparison, Store unique videos to a Common Data Store.

1) Cross Network

Here the Cross Network means association of 2 or more social networking sites. Different videos are uploaded to different sites in the cross network association and only unique videos are uploaded to common data-store.

2) Video to Frame Conversion

The videos are segmented into frames in the form of JPEG images and the frames of the seed video are compared with the frames of the other videos. The duplicate videos are thus eliminated from the database. The videos used are in the .mp4 format. Here create a model social video networking Effective Video Promotion on Cross-Platform networks

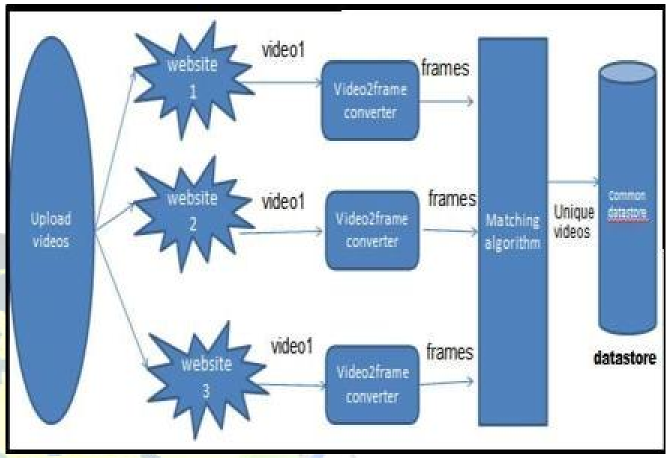

Figure 1: Redundant Video Elimination

Redundant Video Elimination site and use some of the videos present in the database to illustrate the example for duplicate video elimination using content information and context information. This is a very effective method with just a slight loss in the performance. FFmpeg is a library tool that can be used to cut the images from videos. FFmpeg reads from an arbitrary number of input "_les" (which can be regular _les, pipes, network streams, grabbing devices, etc.), specified by the -i option, and writes to an arbitrary number of output "_les", which are specified by a plain output filename. Anything found on the command line which cannot be interpreted as an option is considered to be an output filename. Each input or output _le can, in principle, contain any number of streams of different types (video /audio /subtitle /attachment /data). The allowed number and/or types of streams may be limited by the container format. Selecting which streams from which inputs will go into which output is either done automatically or with the -map option.

Transcoding process

The transcoding process in ffmpeg for each output can be described by the following diagram: FFmpeg calls the libavformat library (containing demuxers) to read input files and get packets containing encoded data from them. When there are multiple input files, ffmpeg tries to keep them synchronized by tracking lowest timestamp on any active input stream. Encoded packets are then passed to the decoder (unless stream copy is selected for the stream, see further for a description). The decoder produces uncompressed frames (raw video/PCM audio/...) which can be processed further by filtering. After filtering, the frames are passed to the encoder,

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which encodes them and outputs encoded packets. Finally those are passed to the muxer, which writes the encoded packets to the output file.

3) Frame Comparison

Feature Extraction

There are three most common characteristics upon which images or videos are compared in content based image retrieval algorithms are Color, Texture, Shape. Color features are defined subject to a particular color space or model. A number of color spaces have been used in journalism, such as RGB, LUV, HSV and HMMD. It is generally believed that human visual systems use texture for recognition and interpretation. In general, color is usually a pixel property while texture can only be measured from a group of pixels.[8] Shape is known as an important cue for human beings to identify and recognize the real-world objects, whose purpose is to encode simple geometrical forms such as straight lines in different directions. Here perform duplicate video detection with various kinds of features is used- Global image features and Entire video based feature for a fast initial search for prospective duplicates, and keypoint based feature are employed for a more refine search.

Algorithm 1 Working Procedure
Input: Video
Output: Similarity Ratio
1: Segment the seed video into frames.
2: Take a video from the set and segment it into frames.
3: Compare the frames of these videos based on the edge value and mean value of images.
4: If both the results are true, then the frames are said to be similar else they are not similar.
5: If all the frames are similar, then the videos being compared said to be duplicate of each other.
6: Take another video from the set. Repeat step 3 to step 5.
7: Repeat the above process for all the videos present in the set.

4) Methods for comparison

The seed video and remaining videos present in the Dominant Version set are segmented. The frames of seed video are taken as taken as input. Frames are compared based on the Edge values and mean value of images. In this module the frame comparison is performed. The seed video and remaining videos present in the Dominant Version set are segmented. The frames of seed video are taken as taken as input. The feature extraction of images produces match value count and following duplicate ratio.

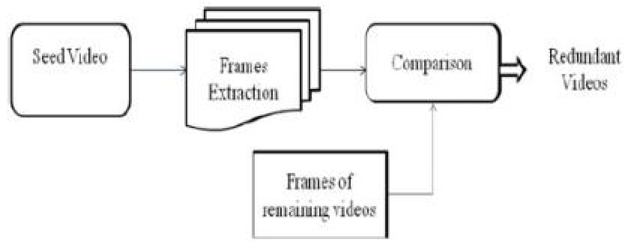

Figure 2: Frame Comparison

The videos are checked for similarity based on the video sequences. The video sequences are checked for similarity based on the levels of temporal resolution, the temporal order, and the temporal duration.

Edge value Detection

Edges and lines in images carry more useful information than other types of features such as texture, colour. Edge detection is a terminology in image processing, mainly for feature detection and feature extraction. This aims at identifying points in a digital image at which the image brightness changes sharply. The discontinuities in image brightness are likely due to discontinuities in depth, discontinuities in surface orientation, and changes in material properties and variations in scene illumination.

Algorithm 2 Edge Value Detection
Input: An image
Output: Edge values of image
1: Take a image.
2: Compute the RGB value for each pixel in the image.
3: From the RGB value compute the luminance value for each pixel.
4: Compare the luminance value of a pixel with its neighbor value.
5: If the luminance value exceeds the threshold value, then an edge is considered at the respective pixel position.
6: Repeat this procedure for all the pixels present in the image.
7: Repeat step 2 to step 6 for all the frames present in the video.

Mean Computation

The mean value of an image is used along with edge value detection to per-form the comparison. The mean of an image is the ratio of sum of its pixel value to its image dimension.

Mean = Sum of the pixel values (H W); Where; H; Ware height and width of the image:

Algorithm 3 Mean Value Computation

Input: An image
Output: Mean value of image
1: Take a image.

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2: Compute the RGB value for each pixel in the image.
3: Find the sum of pixel value.
4: Compute the ratio of pixel value to the image dimension.
5: Stop

5) DATA STORAGE MANAGEMENT

A direct negative impact of video duplication is the extra storage space consumed by duplicate videos. So we have to manage that. When the resulting matching ratio or duplicate ratio is more than a threshold values that video is duplicated. So here the system just update the reference of rst site as that particular video rst uploaded. Otherwise it added directly in the data store[8].

Duplicate Ratio = duplicates found (sampled video duplicates found)

IV. EXPERIMENTAL RESULTS

Using the multi platform online videos can be accessed from far beyond the internal mechanisms of the video sharing portals, such as internal search. Recent studies have found that external referrers, such as external search engines and other social media websites arise to be the new and important portals to lead users to online videos. In this paper, introduce a novel cross-network collaborative application to help drive the online traffic for given videos in traditional video portal. External platform are used to promote and engage with the audiences and distinguished itself with significant information propagation efficiency.

Here the performance evaluation is done using a graph. Duplicate video level in database of both existing and proposed method can be viewed using a graph.

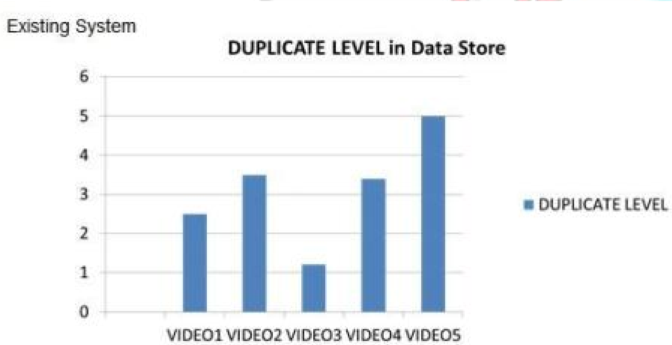

Figure 3: Existing system duplicate video level

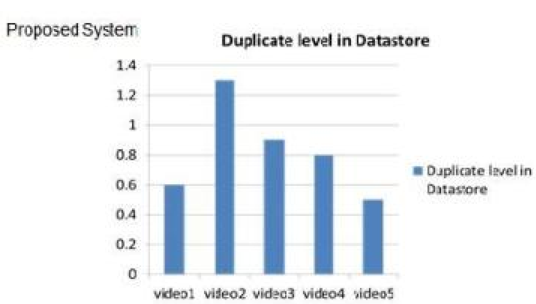

Figure 4: Proposed system duplicate video level

V. RESULT

The system was tested duplicate videos in social media sites .And found that the duplicate level in the data store in proposed system is too small than existing system.

Browse Video File

Figure 5: Video Uploading

After upload a video

Figure 6: After Upload Video

Frame Sequences

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Figure 7: Key-Frames generated

u_id	fname	lname	dob	gender	uname	password
2	radhika	krishnan	7-1-1994	female	radhu	abc
3	ancy	issac	31/05/1991	female	ancy	123
4	seesa	f	31/05/1991	female	seesa	123
5	jissa	s	25/05/1994	female	jissa	123
6	sophiya	mathews	31/05/1991	female	sophi	123
(Auto)	(NULL)	(NULL)	(NULL)	(NULL)	(NULL)	(NULL)

Figure 8: Registration-table

v_id	file_name	date_time	u_id	website	link
1	1.mp4	2016-04-17 13:47:33	3	W1	NA
2	1.mp4	2016-04-17 13:48:17	3	W3	W1
3	3.mp4	2016-04-21 16:17:58	5	W1	NA
4	4.mp4	2016-04-21 16:19:52	5	W1	NA
5	4.mp4	2016-04-21 16:20:44	5	W2	W1
6	3.mp4	2016-04-21 19:34:55	5	W2	W1
7	1.mp4	2016-04-21 19:36:19	5	W2	W1
8	3.mp4	2016-04-21 19:43:57	5	W2	W1
9	9.mp4	2016-04-21 19:46:20	5	W3	NA
10	9.mp4	2016-04-21 22:55:38	3	W3	W3

Figure 9: Video-table

Video found as its rst entry

```
Error: images dimensions mismatch
Match value count: 0
Keyframe C:\Users\hp\Desktop\project u tube\Youtube1\web\key_frames/9_4.png
Match value count: 0
Keyframe C:\Users\hp\Desktop\project u tube\Youtube1\web\key_frames/9_3.png
Error: images dimensions mismatch
Match value count: 0
Keyframe C:\Users\hp\Desktop\project u tube\Youtube1\web\key_frames/9_2.png
Error: images dimensions mismatch
Match value count: 0
Keyframe C:\Users\hp\Desktop\project u tube\Youtube1\web\key_frames/9_1.png
Error: images dimensions mismatch
Match value count :0
Video found to be new ...
```

Figure 10: Match ratio for New video Video found as its duplicate entry

```
Error: images dimensions mismatch
Error: images dimensions mismatch
Error: images dimensions mismatch
Error: images dimensions mismatch
Error: images dimensions mismatch
Keyframe C:\Users\hp\Desktop\project u tube\Youtube1\web\key_frames/1_5.png
Match value count: 0
Keyframe C:\Users\hp\Desktop\project u tube\Youtube1\web\key_frames/1_4.png
Match value count: 0
Keyframe C:\Users\hp\Desktop\project u tube\Youtube1\web\key_frames/1_3.png
Match value count: 0
Keyframe C:\Users\hp\Desktop\project u tube\Youtube1\web\key_frames/1_2.png
Match value count: 0
Keyframe C:\Users\hp\Desktop\project u tube\Youtube1\web\key_frames/1_1.png
Match value count: 0
Keyframe C:\Users\hp\Desktop\project u tube\Youtube1\web\key_frames/13_5.png
diff percent: 0.0
Match value count: 1
Keyframe C:\Users\hp\Desktop\project u tube\Youtube1\web\key_frames/13_4.png
diff percent: 0.0
Match value count :2
Keyframe C:\Users\hp\Desktop\project u tube\Youtube1\web\key_frames/13_3.png
diff percent: 0.0
Match value count: 3
keyframe C:\Users\hp\Desktop\project u tube\Youtube1\web\key_frames/13_2.png
diff percent:0.0
Match value count: 4
Keyframe C:\Users\hp\Desktop\project u tube\Youtube1\web\key_frames/13_1.png
diff percent: 0.0
Match value count: 5
Video found to be duplicate of video id 13
Del vdoC:\Users\hp\Desktop\project u
tube\Youtube1\web\website2/videos/22.mp4
```

VI. CONCLUSION

The duplicate video elimination of the video with help of content and con-text is performed. The time duration acts as alter to avoid unnecessary computation. If the difference of time duration is large, the videos are not compared and regarded as dissimilar. With the thumbnail images, the dis-tance of the colour histogram is computed. These steps lead to pair wise comparison of frames of videos. The mean value of the frame and edge value are used to check the similarity.

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