Characterizing and Predicting the Future Popularity of Online Videos

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ABSTRACT

The big size of video content has been generated on the online web, and user keeping track of all the details requires your complete attention among those videos is spatial arrangement. With the likes hit comment or views. Hence, understanding the popularity characteristics of online videos and predicting the future popularity of individual videos are of great importance. They have direct implications in various contexts, such as service design, advertisement planning, network management, and so on. In this paper, we address those two problems head-on based on data collected from a leading online video service provider in India, namely YouTube. We firstly analyze the characteristics of YouTube video popularity from four key aspects: long-term popularity, video lifetime and early stage popularity. According to this study such as advertisement planning, network management and also view count up to 15 days. Daily growth rate of view count up to 15th days. Aspects: popularity of long-term, hit's video, in public open popularity as well as it demand or reaction on the video.

Keyword: - *Data analysis, CDN (content delivery network), UGC (user generated content), Data mining, CDF (cumulative distribution function), OSN (online social network).*

INTRODUCTION

With the ubiquitous access of Internet and the emergence of Web 2.0 services, an enormous and ever growing amount of online content has been brought into the digital world. Content producers now can reach audiences in inconceivable numbers that are unmatched through conventional channels. Among the various kinds of online content, online videos are currently a dominating component of the Internet. Given the huge amount of video content and the high variability of user attention, it is of utmost importance for a number of tasks to understand the characteristics of online video popularity and further predict the popularity of individual videos. For service providers, the video popularity dynamics and prediction results can greatly benefit their future design of the content filtering, video ranking, and recommendation schemes, which help users to and videos with more potential values more easily. For advertisers in the online marketing, prediction of the next rising star of the Internet can maximize their revenues through better advertising placement. With the extrapolation of video popularity and network operators can proactively manage the bandwidth requirement and deploy the cache servers in the content delivery network (CDN) for hot videos in advance. In this paper, we study the video popularity of YouTube, a leading online video service provider in China. Our work is based on the data of 1,000 videos crawled from YouTube website for 15 *consecutive days. With these data, we analyze in-depth how the popularity of online video content evolves over time, and how to predict the future popularity of an individual video.*

1. LITERATURE SURVEY:

Author has developed-In this system author proposed popular online video-on-demand (VoD) services all maintain a large catalog of videos for their users to access. The knowledge of video popularity is very important for system operation such as video caching on content distribution network (CDN) servers. The video popularity distribution at a given time is quite well understood study how the video popularity changes with time, for different types of videos, and apply the results to design video caching strategies [1].

Author has develop a technique that Understanding the factors that impact the popularity dynamics of social media can drive the design of effective information services, besides providing valuable insights to content generators and online advertisers. Taking YouTube as case study, we analyze how video popularity evolves since upload, extracting popularity trends that characterize groups of videos. We also analyze the referrers that lead users to videos, correlating them, features of the video and early popularity measures with the popularity trend and total observed popularity the video will experience [2].

Author has developed, computer systems are increasingly driven by workload that reflect large scale social behavior, such as rapid changes in the popularity of media items like videos. Capacity planners and system designers must plan for rapid, massive changes in workloads when such social behavior is a factor make two contributions intended to assist in the design and provisioning of such systems analyze an extensive dataset consisting of the daily access counts of hundreds of thousands of YouTube videos. In this dataset, find that there are two types of videos: those that show rapid changes in popularity, and those that are consistently popular over long time periods [3].

Author has developed, previous research on online media popularity prediction concluded that the rise in popularity of online videos maintains a conventional logarithmic distribution. However, recent studies have shown that a significant portion of online videos exhibit sudden rise in popularity, which cannot be accounted for by video domain features alone [4].

Figueiredo et al. characterized the popularity evolution patterns of YouTube videos based on the classification method in, and studied the impacts of different types of referrers on such patterns. Ahmed et al. identified the patterns of temporal evolution for distinct types of data over time and predicted the evolution pattern of popularity in user generated content. Those patterns proposed by the previous works can well describe the evolution of video popularity. However, they focus more on the popularity growth shapes near the (single) peak day. In our study, we complement the definition of popularity evolution pattern, by considering the number and temporal locations of the popularity bursts throughout the whole observation period [5].

2.4 PROPOSED SYSTEM:

This paper focuses on improve future prediction of online videos. To the best of our knowledge, the proposed method is specialize models by popularity evolution patterns in the popularity prediction. A small fraction of videos attract most of the user interest, whereas the vast majority of videos are of limited views. Given the huge amount of video content and the high variability of user attention, it is of almost importance for a number of tasks to understand the characteristics of online video popularity and further predict the popularity of individual videos. For service providers, the video popularity dynamics and prediction result1s can greatly benefit their future design of the content filtering, video ranking, and recommendation schemes, which help users to and videos with more potential values more easily.

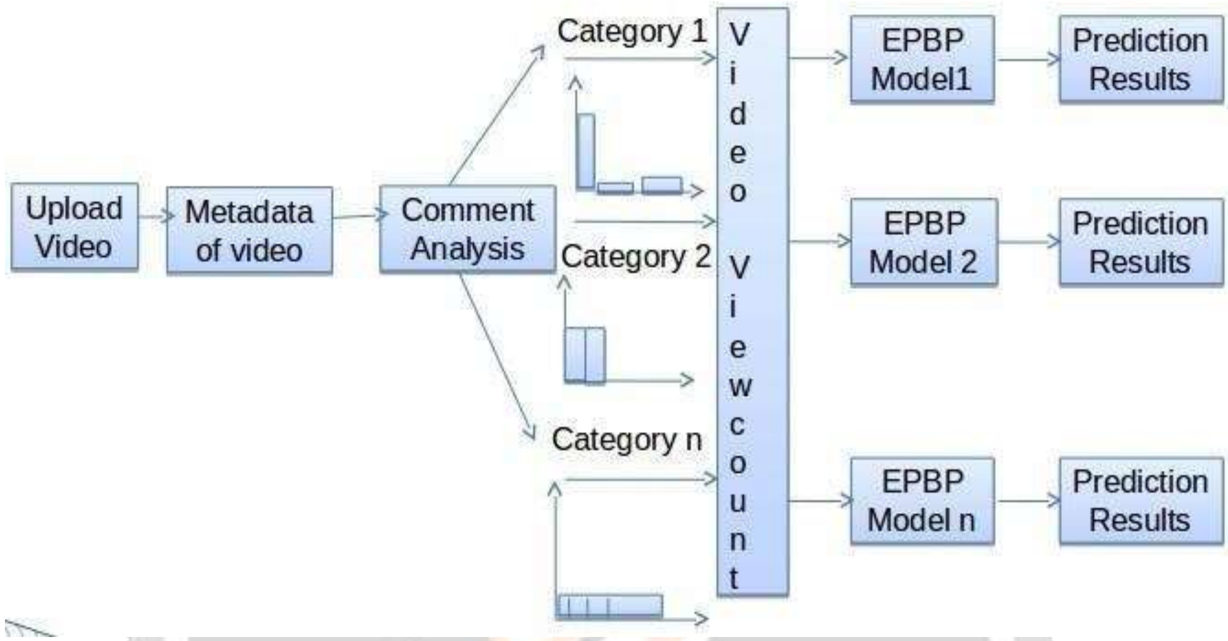

Fig: System Architecture

With the extrapolation of video popularity, network operators can proactively manage the bandwidth requirement and deploy the cache servers in the content delivery network (CDN) for hot videos in advance. In addition, in a quite different context, the video popularity will be of great interest in the opportunistic communications among mobile devices. In such resource constrained environments predicting hot videos is helpful for the content delivering, caching and replicating on the device end. In this system, we study the video popularity, a leading online video service provider. With these data, we analyze in depth how the popularity of online video content evolves over time, and how to predict the future popularity of an individual video. The main contributions of our work are summarized as describe. We provide a detailed characterization of the popularity dynamics of online videos. In particular, we provide insights into the popularity evolution patterns of the individual videos. We tackle the problem of popularity prediction by proposing a model that can capture the popularity evolution of an individual video. To the best of our knowledge, the proposed method is specialize models by popularity evolution patterns in the popularity prediction. We evaluate our model on a real world dataset and compare the prediction performance with two state of the art online video popularity prediction models.

2.5 VIDEO LIFETIME FOR ALL VIDEOS:

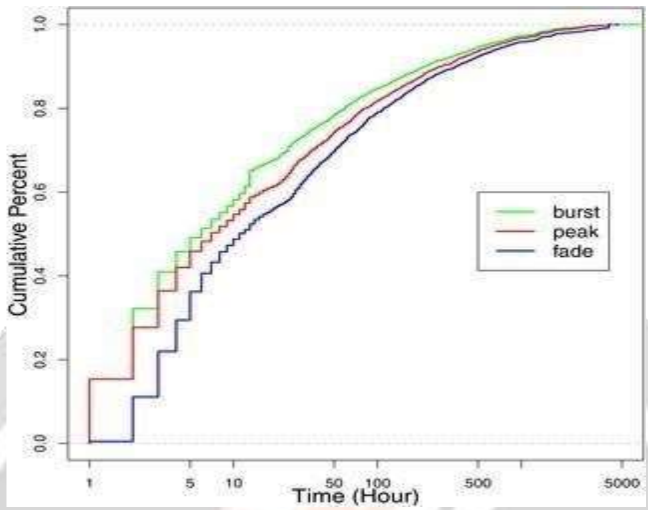

Fig. Graph for video lifetime

4. CONCLUSION:

In this paper, we firstly carried out a detailed characterization study of the video popularity dynamics, based on the dataset crawled from YouTube for 15 consecutive days.This system carried out a detail characterization of the video based on the dataset. Found the distribution of long-term video popularity. System analysed the distribution of videos lifetime in our dataset and also find the linear correlation between the early view count and the long-term view count. We analyzed the distribution of video lifetime in our dataset, and found differences between the videos with different popularity. We then revealed how the popularity of an individual video evolved over time, considering the number and temporal locations of popularity bursts.

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