Social-Aware Video Delivery: Challenges, Approaches, and Directions

Zhi Wang, Jiangchuan Liu, and Wenwu Zhu

Abstract

We have recently witnessed the convergence of online social network services and online video services: users import videos from content sharing sites, and propagate them along the social connections by re-sharing them. Such social behaviors have dramatically reshaped how videos are disseminated, and users are now actively engaged as part of the social ecosystem, rather than being passive consumers. Despite the increasingly abundant bandwidth and computation resources, the ever increasing data volume of user generated video content and the boundless coverage of socialized sharing have presented unprecedented challenges. This article first presents the challenges in social-aware video delivery. Then we present a principal framework for social-aware video delivery and a state-of-the-art overview of approaches. Moreover, we identify the unique characteristics of social-aware video access and social content propagation, and reveal the design of individual modules and their integration toward enhancing users' experience in the social network context. Finally, we discuss future research directions.

In the past decade, we have witnessed the fast evolution toward new generation networked multimedia processing and sharing in the Web 2.0 era. Today, high-definition videos and even 3D/multiview videos can readily be captured and browsed by personal computing devices, and conveniently processed and stored with remote cloud resources. Users are now actively engaged as part of a social ecosystem, rather than passively receiving media content. The revolution is being driven further by the deep penetration of third/fourth generation (3G/4G) wireless networks and smart mobile devices that are seamlessly integrated with online social networking and media sharing services.

Despite the increasingly abundant bandwidth and computation resources, the ever increasing data volume of user generated video content and the boundless coverage of socialized sharing have presented unprecedented challenges to both content and network service providers. The highly diversified content origins and distribution channels further complicate the design and management of online video sharing systems. This article presents a state-of-the-art survey on social-aware video delivery, identifying the key issues and presenting solutions toward this promising research direction.

Background and Challenges in Social Video Delivery

Online social network services connect users through "friendship" (e.g., Facebook), "following" relationships (e.g., Twitter), or professional connections (e.g., LinkedIn). Such applications have successfully changed how people are connected to each other and how they share information, including video. We have recently seen the convergence of online social network services and online video services: users can "import" videos from video sharing sites to online social networks, and make the videos propagate along social connections by *re-sharing* them. The social behaviors have dramatically reshaped how videos are disseminated to users: *people are now receiving videos from friends directly*. For example, the online video clip "Gangnam Style" attracted over 1 billion views in 6 months after it was uploaded due to its propagation over popular online social networks including Twitter and Facebook. Today, 500 years worth of video are watched and shared every day by Facebook users, and over 700 videos are shared on Twitter each minute [1].

Conventional video delivery strategies, for example, the original client/server streaming, IP and application-layer multicast/peer-to-peer, and content delivery networks (CDNs), mainly focus on improving the network delivery performance so as to meet the increasing scale of video requests. They have generally assumed that the content comes from centralized service providers, and the users only *passively* receive the contents [2]. For videos shared over social networks, however, the access patterns are much more dynamic, being affected by individuals and their activities during propagation. With information propagation, the scale/coverage in the social network context can be much larger and broader [3], making the system design much more involved.

More specifically, we are facing the following challenges in social video delivery.

C1: Users Instead of Service Providers Determine How Videos Reach Each Other: In an online social network, contents are generated, propagated, and disseminated by users. In 2014, YouTube reported that over 100 hours of video clips were uploaded by users every minute. Content delivery systems thus have to distribute a much larger volume of user-generated videos than what has ever been handled by conventional content providers [4]. Second, users share videos through social connections, and they tend to receive videos from their friends. As such, a content service provider no longer has tight and centralized control over the dissemination of contents.

C2: Dynamic Content Propagation: Social propagation is affected by a combination of factors, including social topology,

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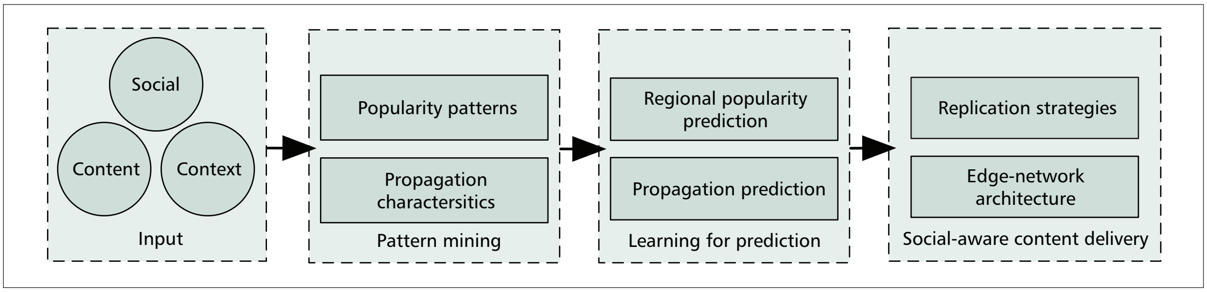

Figure 1. Framework of social-aware video content delivery.

user behaviors, and inherent content characteristics, to name a few [5]. Given the many influential factors, propagation is highly dynamic, and traditional content delivery strategies generally lack prediction tools to infer such inherent dynamics.

C3: Change of Social Content Popularity: The changes in content origin and social propagation also change the popularity distribution of videos. On one hand, the overall skewness of social video popularity distribution has been amplified; on the other hand, certain unpopular videos can be re-identified and then shared among users with close social relations. Video popularity is a key factor in designing and optimizing video delivery systems, and the change thus has strong implications. For example, it has been observed that the request hit ratio can be degraded by over 70 percent when traditional cache strategies were used to handle online social contents [6].

Social-Aware Video Delivery Framework

These challenges demand a joint study on user behaviors, social video popularity, and social propagation to enhance the video content delivery in the social network context. To this end, Fig. 1 illustrates a general framework of social-aware video content delivery. This integrated framework takes the social, content, and context information as the input to mine the popularity patterns and propagation characteristics. Machine learning models are designed to predict the evolution of social video popularity and the propagation patterns (e.g., the size of a social cascade). The prediction reveals how videos would be shared in different regions, and the network resources can then be adaptively allocated among these regions. Content replication and caching strategies will be incorporated as well to further improve the sharing efficiency [7].

We next check the unique characteristics of social-aware video access and social content propagation, and closely examine the design of individual modules and their integration in the framework.

Social Video Popularity: Distribution, Evolution, and Prediction

We start from the popularity of videos propagated through online social networks, including the distribution, evolution, and effective prediction.

Popularity Distribution and Evolution

To investigate the distribution of social video popularity, we use a real-world dataset from Renren (one of the largest online social networks in China), which recorded one-week traces covering 3 million users issuing 11 million video shares and 87 views [8]. We observe that about 2 percent of the most popular videos attract over 90 percent of the views, compared to 20–90 percent in statistics in conventional video sharing systems like YouTube [4], where social propagation is not as common as in Renren.

Since there is a large fraction of unpopular social videos, we further investigate in which types of social groups these unpopular videos propagate, using a Weibo (a Twitter-like social network) dataset that provides traces recording 400,000 videos shared by users in one month. By randomly sampling 50 videos with different propagation size (the number of users involved in a video's propagation), we explore the correlation between the propagation size and the clustering coefficient (larger clustering coefficient indicates close connection between members) of the social group formed by the users involved in the propagation. In Fig. 2, each sample illustrates the video propagation size vs. the clustering coefficient of the corresponding social group. We observe a relatively strong correlation between the propagation size and the clustering coefficient; that is, unpopular videos tend to be shared among small social groups that are closely connected (socially).

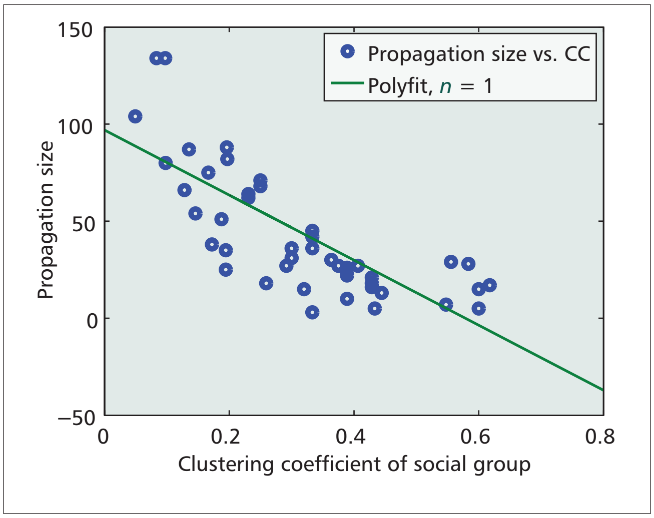

Figure 2. Unpopular videos tend to be shared in small social groups with members closely connected.

Our data analysis also reveals two interesting observations on the popularity evolution of social videos, which noticeably differ from traditional video access patterns:

- Fast popularity decay for unpopular videos (e.g., 30 percent of least popular videos). Unpopular videos only attract some users on the first day. After that, their popularity decreases extremely quickly. This observation indicates that the lifetime of many unpopular videos is less than one day, and users in the online social network will soon lose interest in these videos in their social communities;
- Delayed peak access and long lifetime for popular videos. For highly popular videos (e.g., top 2 percent in popularity), their peak access generally arrives after two or three days, and the popularity remains at a high level for a relatively long period (e.g., several weeks) [8].

Social Popularity Prediction

The above observations suggest that content delivery mechanisms need to be substantially revised, and the social-related factors (e.g., the total number of previous views and the video

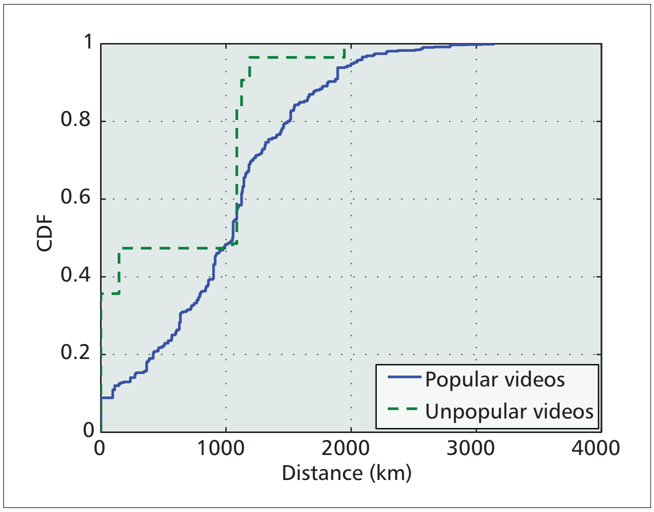

Figure 3. CDF of distance between users that are sharing in the same propagation of social videos

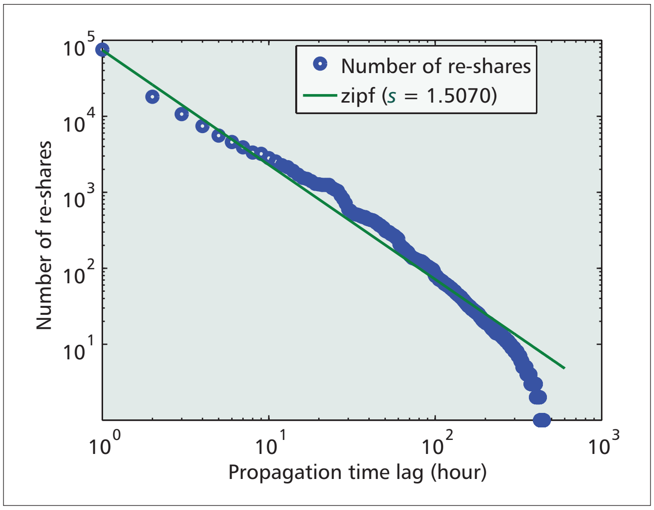

Figure 4. Number of re-shares vs. the time lag.

age) will play important roles [9]. In particular, the popularity prediction has to jointly consider both *accuracy* and *timeliness* of the prediction results.

As shown in [8], each video can be assigned with an index $k \in \{1, 2, \ldots, K\}$ according to the absolute time t^k_{init} when the video is initiated. Once a video is shared, it will be propagated through the social network for some time duration. A video has an age of $n \in \{1, 2, \ldots\}$ periods if it has been propagated through social media for n periods. In each period, the video is further shared and viewed by users depending on the sharing and viewing status of the previous period. The propagation characteristics of video k up to age n are captured by a d_n-dimensional vector $\mathbf{x}^k_n \in \mathcal{X}_n$, which includes information such as the total number of views, and other contextual information such as the characteristics of the social network over which the video propagates.

Social media popularity prediction can then be formulated as a multi-stage sequential decision and online learning problem [8]. Using multi-level popularity prediction in an online fashion, such social-aware prediction outperforms existing view-based approaches by more than 30 percent in terms of prediction reward — a trade-off between popularity prediction accuracy and timeliness. In summary, social relationships, user behaviors, and content characteristics all affect the social media popularity, and its prediction relies on understanding of dynamic social media propagation.

Dynamic Social Video Propagation

Popularity reflects the macroscopic aggregated views of the videos shared. We next have a closer look at the social propagation process for videos, which determines how individual videos reach different users in online social networks.

The generation and re-sharing of a social video typically form a propagation tree, rooted at the user who generates the video or initiates the sharing (referred to as the *initiator* or *root*). We refer to users who re-share the video as *spreaders*, and users who receive the shared video as *viewers* (or *receivers*). A video's popularity can then be calculated as the sum of its spreaders and receivers.

Besides the normal nodes that view and share videos, there are two types of nodes that are worth noting:
- Super spreaders in propagation, which are followed by many viewers. The super spreaders and especially those appearing in the early propagation stage generally play an important role in the further "explosion" of the propagation (i.e., attracting many viewers).
- Free riders in propagation, which do not share videos at all and indeed consist of a large portion of the viewers. They only consume videos shared by others.

Models have been developed to capture social media propagation. Given the different types of nodes, a susceptible-infectious-recovered (SIR) model can be used to model social video propagation, which considers a fixed population with three compartments: *susceptible*, *infectious*, and *recovered*. Li *et al*. [10] particularly investigated an extended epidemic model to capture the video propagation in online social networks:

Initially, a user shares this video from an external video sharing site, and this initiator becomes infectious. All other users in the social network are safe except the friends of the initiator. The shared video appears in the news feed of the initiator's friends, and thus they become susceptible. After a while, these friends log into the social network gradually and decide whether to watch the video (*infected*) or not (*immune*). For those infected users, they will decide whether to share after watching the video. They become recovered if they choose not to share, and they become infectious if they choose to share. Again, these infectious users will make their friends who are in the safe stage become susceptible.

Based on the propagation model, the parameters can be trained using real propagation traces, and the connection between video access and social activities is created for content delivery strategies.

Large-scale measurement studies have also discovered interesting locality patterns in the propagation structures [11].

Geographical Locality

A large fraction of the videos are shared between users who are geographically close to each other. In Fig. 3, we plot the CDF of distances between users who join the social propagation of the same video in the online social network. Different curves are for videos with different popularities:
- Popular videos: videos with popularity in the top 2 percent
- Unpopular videos: videos with popularity in the bottom 30 percent

We observe that different from traditional video consumption, unpopular social videos tend to be shared in local regions, where users are near to each other. For example, around 40 percent of the distances between users sharing the same unpopular videos are close to 0 km.

Temporal Locality

In an online social network, users are more likely to re-share new videos, that is, videos that are recently imported or re-shared. Figure 4 illustrates the number of re-shares of a video in a timeslot (1 h) vs. the time lag since the propagation.

We observe that most of the re-shares happen in recent hours, and the re-share number against the time lag follows a Zipf-like distribution with a shape parameter $s = 1.5070$. More than 95 percent of the re-shares happen within the first 24 hours. This indicates that in social video sharing, users' behaviors are highly crowded around the time point when it is imported.

Cheng *et al.* [12] further studied the propagation structure of social videos and identified a series of representative structures. We define a branching factor as the number of viewers who directly follow a spreader, and a share rate as the ratio of the viewers who re-share the video after watching it. An interesting observation is that the branching factor and share rate is level-independent: the branching factor and share rate are merely correlated to users' distance (the number of social hops) to the root. As such, the branching factor and share rate can be set the same for all spreaders and viewers, regardless of the social distance to the root.

In summary, social propagation determines how online social videos dynamically reach users in today's Internet. Depending on the characteristics of the social media services, different propagation models can be developed to design strategies for social media distribution.

Social-Aware Video Content Delivery

Given the unique characteristics of social videos, a series of solutions have been proposed in the literature addressing the challenges in different aspects.

Propagation-Based Social Video Replication

A significant amount of effort has been devoted to utilizing social information to enhance the strategies in traditional content delivery (e.g., CDNs, peer-to-peer networks). Wang *et al.* [11] proposed a hybrid CDN and P2P architecture for social video distribution, where the CDN servers can support the time-varying bandwidth and storage allocations requested by different regions, while peers are able to help contribute to each other in similar social groups.

In this replication architecture, two overlays exist in the social-aware replication design (as illustrated in Fig. 5):

- *Social propagation overlay* based on the social graph, which determines the video propagation among friends. That is, users, after generating a video, can share the video with their direct friends, who will further re-share the video to more people.
- *Delivery overlay* determines how video contents are delivered from edge-cloud servers to users or among themselves in a peer-assisted paradigm.

Geographic Influence Index

The replication is designed to take social propagation into account. When performing video replication, we need to find out the videos that may propagate to more regions in the future. We design a geographic influence index in the region prediction for that, as below:

$$g_v^{(T)} = c_1 \log(c_2 s_v^{(T-1)}),$$

where $s_v^{(T-1)}$ is the propagation size of the propagation tree of video v in time slot $T - 1$. Parameters c_1 and c_2 are selected to fit the measurements. $g_v^{(T)}$ approximates the number of regions to which the video will propagate in the future time window, according to our measurement studies. Intuitively, a video should be replicated to more regions when the predicted number of regions involved in the propagation is larger than the number of regions to which it has already been replicated (θ). Based on the geographic influence index, we can predict whether the regions where the video has been replicated are

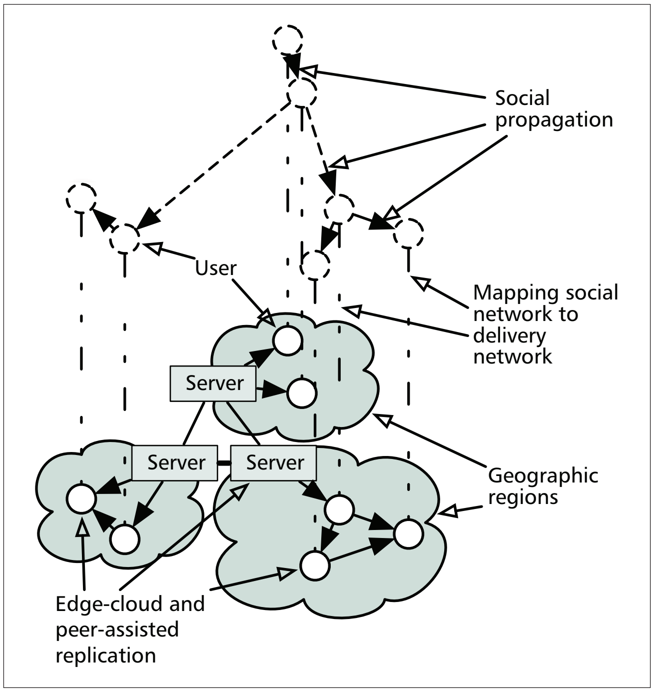

Figure 5. Edge-cloud and peer-assisted replication based on social propagation.

enough. To proactively replicate social videos, a video with a geographic influence index $g_v^{(T)} > \theta$ should be replicated to more regions to serve users locally. Furthermore, we use the locations of leaf users in the propagation tree to predict to which regions the video should be replicated.

Crowdsourced Caching for Mobile Social Videos

By replicating bandwidth-intensive video copies on the *edge-network* devices (e.g., users' smartphones) to enable users to serve each other, crowdsourced caching is promising for social media distribution. Previous studies have demonstrated that such device-to-device (D2D) content sharing is possible when users are close to each other, and the contents to be delivered by users are delay-tolerant [13]. However, in traditional D2D content sharing, a user broadcasts generated contents or reshared contents to a set of random users that are close to it. As a result, all contents are disseminated to users in the same way (e.g., random flooding), causing the following problems:

- In greedy flooding, smart devices in edge networks have to spend expensive power to cache and relay excessive contents. For the increasing number of user-generated social contents, such a mechanism is inherently unscalable.
- Social videos have heterogeneous popularity, while the conventional approaches treat them all the same, resulting in resource waste in handling unpopular contents.
- Due to the dynamic mobility patterns, users may not be able to fetch contents quickly, resulting in poor quality of experience.

To address these issues, a joint propagation- and mobility-aware crowdsourced replication strategy is developed based on social propagation characteristics and crowd mobility patterns in edge-network regions, for example, an area of 100 m range across which users can move. As illustrated in Fig. 6, using the social graph and propagation patterns, we first estimate how contents will be received by users, and then we predict to which regions the users will move and how long they will stay. Instead of letting contents flood between users who are merely close to each other, we disseminate social videos according to the influence of users and the propagation of videos. In this example, user e — while not a friend of any other

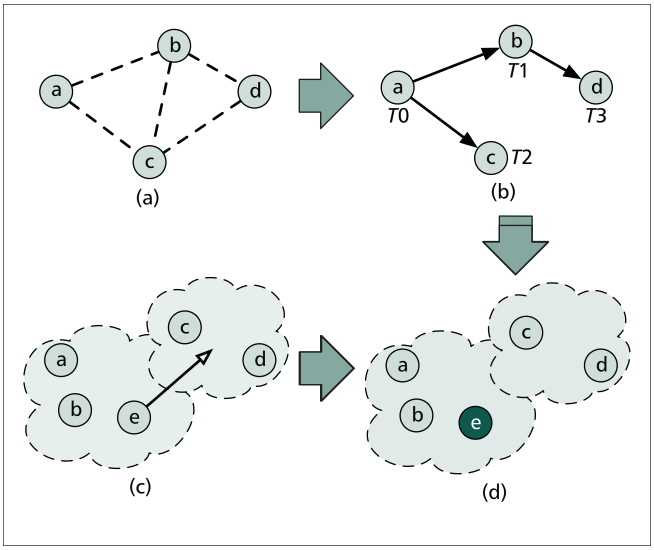

Figure 6. Crowdsourced replication affected by: a) social topology; b) content propagation; c) user regional mobility; d) off-grid replication assignment.

user — is moving to the region where users *c* and *d* are. Thus, *e* will be selected to replicate the content generated by user *a*, and both users *c* and *d* will receive the content shared by user *a* in the social propagation at times *T*2 and *T*3, respectively.

Geo-Distributed Cloud Video Distribution

Geographical information is useful when we move toward cloud platforms. We have seen many new generations of cloud-based multimedia services emerging in recent years, which are rapidly changing the operation and business models in the market. A prominent example is Netflix, which migrated its entire infrastructure to the powerful Amazon Web Services (AWS) cloud in 2012, using Elastic Cloud Computing (EC2) for transcoding master video copies and Simple Storage Service (S3) for content storage. Several works also study using the cloud resource for social content delivery; for example, Wu *et al*. [14] considered a generic geo-distributed cloud infrastructure, which consists of multiple cloud sites distributed in different geographical locations. Social video contents can be replicated very close to users using the geo-distributed cloud resource.

Instant Social Video Delivery

With the rapid development of mobile networking and end terminals, anytime and anywhere data access has become readily available nowadays. Given crowdsourced content capturing and sharing, the preferred length is becoming shorter and shorter, even for such multimedia content as video. Representatives including Twitter's Vine and Tencent's Weishi enable users to create ultra-short video clips, and instantly post and share them with their followers. Taking Vine as a case study [15], Zhang *et al*. showed that instant social videos have short lifetimes and highly skewed popularity that quickly decays over time. Videos in these social trending media become more fragmented and instantaneous — driven by the paradigm shift to mobile and cloud computing. The result indicates that a middleware framework integrated with a pre-fetching and watch-time scheduling scheme is promising to provide improved quality of experience.

Summary and Future Direction

With the advances in online social networking, users, instead of content providers, determine how videos reach each other. Such key characteristics of networked videos as the popularity distribution and its evolution have been strongly affected by the social behaviors of users, challenging traditional content delivery that considers users only as passive consumers. This article surveys recent works on social video delivery toward improving the quality of experience of mass users. We have identified the unique patterns and characteristics of social video propagation and content popularity through large-scale trace data analysis. We have demonstrated a series of strategies with great potential, including content replication, crowdsourced content caching, and network resource allocation. This new and promising research area opens many challenging issues to be addressed in the near future, and we believe that a data-driven and social-aware framework design will be the key. Within this framework, deep understanding of user behaviors and social propagation structures, knowledge of content characteristics and context information, as well as social-relationship-based collaborative content sharing mechanisms will all play important roles.

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References

[1] Youtube, http://www.youtube.com/yt/press/statistics.html.
[2] Z. Wang *et al.*, "Joint Social and Content Recommendation for User Generated Videos in Online Social Network," *IEEE Trans. Multimedia*, vol. 15, no. 3, Apr.l 2013, pp. 698–709.
[3] J. Pujol *et al.*, "The Little Engine(s) that Could: Scaling Online Social Networks," *ACM SIGCOMM Comp. Commun. Rev.*, vol. 40, no. 4, 2010, pp. 375–86.
[4] M. Cha *et al.*, "I Tube, You Tube, Everybody Tubes: Analyzing the World's Largest User Generated Content Video System," *Proc. ACM SIGCOMM*, 2007.
[5] Z. Wang *et al.*, "Enhancing Internet-Scale Video Service Deployment Using Microblog-based Prediction," *IEEE Trans. Parallel Distrib. Sys.*, vol. 26, no. 3, Mar. 2015, pp. 775–85.
[6] A. Mislove, "Rethinking Web Content Distribution in the Social Media Era," *Proc. NSF Wksp. Social Networks and Mobility in the Cloud*, 2012.
[7] R. Torres *et al.*, "Dissecting Video Server Selection Strategies in the YouTube CDN," *Proc. IEEE Int'l. Conf. Distrib. Computing Sys.*, 2011.
[8] J. Xu *et al.*, "Forecasting Popularity of Videos using Social Media," arXiv preprint arXiv:1403.5603, 2014.
[9] Y. Borghol *et al.*, "The Untold Story of the Clones: Content-Agnostic Factors that Impact YouTube Video Popularity," *Proc. ACM SIGKDD Conf. Knowledge Discovery and Data Mining*, 2012.
[10] H. Li, X. Cheng, and J. Liu, "Understanding Video Sharing Propagation in Social Networks: Measurement and Analysis," *ACM Trans. Multimedia Comp., Commun., and Applications (TOMM)*, vol. 10, no. 4, 2014, p. 33.
[11] Z. Wang *et al.*, "Propagation-Based Social-Aware Replication for Social Video Contents," *Proc. ACM Int'l. Conf. Multimedia*, 2012, pp. 29–38.
[12] X. Cheng, H. Li, and J. Liu, "Video Sharing Propagation in Social Networks: Measurement, Modeling, and Analysis," *Proc. IEEE INFOCOM*, 2013.
[13] X. Wang *et al.*, "Toss: Traffic Offloading by Social Network Service-Based Opportunistic Sharing in Mobile Social Networks," *Proc. IEEE INFOCOM*, 2014, pp. 2346–54.
[14] Y. Wu *et al.*, "Scaling Social Media Applications into Geo-Distributed Clouds," *Proc. IEEE Int'l. Conf. Distrib. Comp. Sys.*, 2012.
[15] L. Zhang, F. Wang, and J. Liu, "Understand Instant Video Clip Sharing on Mobile Platforms: Twitter's Vine as a Case Study," *Proc. ACM Network and Op. Sys. Support on Digital Audio and Video Wksp.*, 2014.

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