SocialTube:P2P-Assisted Video Sharing in Online Social Networks

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Abstract:-Video sharing has been an increasingly popular application in online social networks. However, its sustainable development is severely hindered by the intrinsic limit of the client/server architecture deployed in current OSN video systems, which is not only costly in terms of server bandwidth andstoragebutalsonotscalablewiththesoaringamount ofusersandvideocontent.ThepeerassistedVideoonDemand(VoD)technique,inwhichparticipatingpeersassisttheserverindelivering videocontenthas been proposed recently. Unfortunately,videos canonlybedisseminatedthrough friendsinOSNs. Therefore, current VoDworksthatexploreclusteringnodeswithsimilarinterestsorcloselocationforhighperformanceaaresuboptimal,ifnotentirelyinapplicable,inOSNs. Based onourlong-term real-world measurementof over 1,000,000usersand 2,500 videos onFacebook,weproposeSocialTube,anovel peer-assistedvideosharingsystemthatexplores social relationship,interestsimilarity,and physical locationbetweenpeersin OSNs. Specifically, SocialTubeincorporatesfouralgorithms: a social network (SN)-basedP2P overlay construction algorithm, ASN-based chunkprefetchingalgorithm,chunkdeliveryand schedulingalgorithm, and abuffermanagementalgorithm.Experimentalresultsfrom aprototypeonPlanetLaband anevent-drivensimulator showthatSocialTube can improvethequalityofuser experienceand system scalabilityovercurrent P2P VoDtechniques.

1 INTRODUCTION

Online socialnetworks(OSNs) (e.g.,Facebook, Twitter) arenow amongthe most popularsites on the Web. An OSNprovides a powerful means of establishing social connectionsand sharing,organizing, and finding content.For example,Facebook presently has over 500 million users. Unlike currentfile or video sharing systems (e.g., BitTorrent and YouTube), which are mainly organizedaroundcontent,OSNs are organized around users. OSNusers establishfriendshiprelationswith realworld friends orvirtualfriends, and post their profiles and contentsuch asphotos,videos, and notes to their personalpages.

In order to investigate the video watching behaviors of users in OSNs, we queried more than 1,000,000 users and retrieved about 2,500 public visible videos meta data on Facebook. Our measurement reveals that (1)most of the viewers of a user's videos are the user's close friends, (2)most video views are driven by social relationships, and the rest are driven by interests, and (3) viewers of the same video tend to reside in the same location. Based on our observations, we propose Social Tube, a system that explores the social relationship, interest similarity and location to enhance the performance of video sharing in OSNs. Specifically, an OSN has a social network (SN)-based P2P overlay construction algorithm that clusters peers based on their social relationships and interests. Within each cluster, nodes are connected by virtueof their physicallocation in order to reduce video transmission latency. SocialTubealsoincorporates anASN-basedchunkprefetchingalgorithmto minimize video playbackstartupdelay. We have conducted extensiveexperimentsin anevent-driven simulatorand implementedaprototype on PlanetLabtoevaluatethe performanceof Social Tube. Performanceresultsshow that SocialTube greatly reduces the workload of the server, improves the quality of playback, and scales well to a large client population. In thesupplemental material,we presenta chunk delivery and scheduling algorithmandabuffermanagementalgorithmtofurther enhancethe performanceofSocialTube.

Toour knowledge,this work isthe first that studies thedistinctcharacteristicsof OSN video sharing that vary from other content-basedsystem-wide video sharing, and buildsa P2P-basedvideo sharingsystem in an OSN by leveragingthose characteristics for higher performance.Our previousconferenceversion of this article [22]introducesthe basic trace data analysis and design of SocialTube. This articlepresents more trace data analyticalresults.Italso presents new SocialTubemechanismsincluding locality-aware video prefetching mechanism,two policies to increase the chunk delivery abilities, and buffer management algorithm. Thisarticle furtherpresentsmore simulationresults and the experimentalresultsfortheSocialTubeprototypeontherealworldPlanetLabtest bed.

2 FACEBOOKMEASUREMENTANDANALYSIS

Inthis section, wepresentour Facebook trace measurementresultsandgive an in-depthperspectiveof Facebook video viewingpatterns,that shows the necessity ofpeerAssistanceinOSNvideo sharing and provides a directionforthe designofaP2Pvideo sharingsystem in OSNs. We used breadth-first-search [23] to query over 1,000,000users seededby5users inthe USA.In order to avoid overloadingthe Facebook, we sent a query to Facebook every 5s.Wecanonly seethe video activities ofthe users who arefriendsorFOFsofthecrawler and the users that chose “everyone” as their video access option.Becauseofthisaccesslimit,weonlyfoundabout 2,500videos and 12,000users who watched these videos duringthe time periodfrom Jul. 2007 to Aug. 2010, which isused as a samplefor the video sharing and watching activities.The collecteddatasetincludes the information about userfriendshiprelations, interests, locations, and videos uploadedand sharedby users. Foreach video, weretrievedthevideo metadatasuchas itstitle, length, and viewerswhen available.Torespect the privacyof the users, weanonymizethe user names beforestoringthe data inourdatabase.Weonlycrawled the videometadataof these users, with other personal informationuntouched.

2.1 Popularity ofVideosonFacebook

First, we investigate the popularity of videos on Facebook over the years number of videos Corresponding to the time they are uploaded in our collected video pool. It shows that the number of videos uploaded to Facebook increases sharply along with time. Since Facebook launch edits video service in 2007, the increasing trend of video uploading has never slowed down, making it one of most popular applications on Facebook the video length Distribution in our collected video pool.

2.2 Effect ofSocialDistanceon Video Viewing Patterns

Socialdistancebetweentwo usersinthesocialnetworkgraphrepresentsthe closenessof their relationship. If two users are directlyconnectedin the social network, theirsocialdistanceis1;ifoneuserisafriend of another user’sfriend, then the social distancebetween them is 2,and soon. Next, weinvestigatethe impact of social distanceonuser video viewingpatterns.

We call the viewers who have watched almost all videos of a user the user’s followers, and call other viewers non-followers. We use a thresholdThfor the percentofallthevideos ofauser that aviewer watches in order tobecome afollower,and set Th=80% inthis analysis.

2.3 EffectofInterest onVideoViewing Pattern

Next, we explore the correlationbetweenuser interests andvideo viewingpatterns.We selected a sample of 118distinctusers that watched more than one video fromourdatasetandmanuallyclassifiedthe videos they watchedinto19interest groupsbased on video content. The 19interestgroupswere determined based on the video categoriesinYouTube suchasgaming, rock music and action movie. Foreach user, wecalculatedthe percentageofviewed videos ofeach interestgroup. Then, werankedthese 19 interest groups in descending order ofthepercentagevalues. Wecalculated the average percentagevalue ofthe118users foreach interest group rank and show the result. Weobserve that, onaverage,46%ofvideos auserwatchedareon his/her top 2 interests topics, 79% of videos a user watched are on his/hertop 3intereststopics, and 94%are on his/her top 4interests topics.

2.4 Effect ofPhysical Locationon Video ViewingPatterns

Wealsoanalyze thegeographicallocations ofusers whoviewthe same videos in order toseewhether location canalsobeleveragedforvideosharinginOSNs.In Facebook, someusersinputtheircurrentresidentcityintheir profiles. Because manyfriend relationships in Facebook areconnectedbyoffline relationship,such as classmates orcolleagues,this producesastronglocation clustering effect.Thisresult conformstotheobservationinthat most ofthe wall posts aresent withinlocalphysical region. Thiseffectcould makeP2Pvideo sharing systems in OSNs more efficient byenablinggeographicallyclose nodes to share videos betweeneach other.

2.5 Active Life Period of Videos

We measuredthe percentage of views of a video in eachmonthafterthevideo isuploaded outofallviews. Wefound that videos in Facebook have an active life period of about onemonth.Viewsinthisperiodaccountfor more than 90percentofallviews. After onemonth,there are onlyoccasional views.

3 THEDESIGNOFSOCIALTUBE

The Facebook measurement video sharinginFacebook isincreasinglypopular (O1) and maygenerateaheavy burden on the video server (O2).Fortunately,the length oftime that the users stay onlineinFacebook israpidlyincreasing(O3), enabling the possibilityforP2Pvideo sharingamong the online users themselves.Therefore,P2P-assisted video sharingisapromisingstrategyin OSNs. Based onobservations O4-O10onthecharacteristicsof video viewer behavior InFacebook,weproposeSocialTube,aP2Pvideosharing systemforOSNs.

We firstintroducethe basic conceptsand strategiesused inSocialTube. InFacebook, eachnode can upload avideo totheFacebook video server oranexternallink toa video from anexternalserver. Inthispaper,weuse *server*to representall video source servers, including both Facebook and externalvideo servers. Similar tocurrentpeer-assistedcontentdeliverymechanisms, the peers inSocialTubestore videos they have watchedpreviouslyfor video redistribution.InSocialTube, a video isdividedinto small chunkswith afixed size.

Incurrent video sharinginFacebook, anode alwaysrequeststheserver for videos uploadedbysource nodes. Welet the server keep track of the video watching activities ofviewersofaspecific source node in order to identify and updateits followers and non-followers based on SocialTube'spre-definedthresholdsof*Tl*and *Th*. This dutycan beassignedtothe source node itself if it has sufficient capacity. The nodes in the system will periodicallyreporttheir video providing activities totheserver. When theserver determinesthat a peer is afollowerofthesource node, itnotifies the source node, which notifies allnodes initsswarmsabout the follower. Consequently,thefollowerbecomes amemberofeach of theswarms, and allswarm-peers ineachofthe swarms connect toit.When theserver determinesthat apeer is anon follower ofthesource node, theserver determines itsinterestsbased onthecontents ofvideos the peer visited, andnotifies thesource node about the non-follower along with its interests.The source node then notifies the peers in the clustersof the interestsof that non- follower,andnotifies thenon-followerabout theclusters. Thenonfollowerconnectstoallfollowersandthe source and toafewphysically closenodes ineachcluster.

Toreducethevideo startuplatency, weproposea push- based video prefetching mechanism in Social Tube. In SocialTube, when a source node uploadsa new video to the server, italso pushesthe prefix (i.e.first chunk) of the video toitsfollowersand tothe interest-cluster- peers in theinterest clustersmatching the content of the video. The prefixreceiversstore the prefix in their cache. Those interest cluster-peersand followers who are not online when the source node pushesthe prefix will automatically receive it from the source node or theserver oncethey come online. After thesource node leaves, the responsibilitytopush the prefix falls tothe server. Since these followersand interest cluster-peers are very likely towatch the video, the cached prefixes have ahigh probabilityofbeing used.

Once the nodes requestthe videos, the locally storedprefix canbeplayed immediately withoutdelay. Meanwhile,the nodetries to retrieve the remaining video chunksfrom its swarm peers.Similar toBitTorrent,SocialTube allows arequestertorequest 4online nodes at the same time toprovidethe video contentin order to guaranteeprovideravailability and achieve low delay byretrievingchunksinparallel. Itfirstcontacts interestcluster-peers,then followers,then thesource node. If the requesterstill cannot find 4providersafter the source node is contacted,it resorts to the server as the only provider.Consideringthe high capacity of the server, the requesterdoes not need to have 4providers if it has the server as a provider.This querying order can distributetheload ofchunk deliveryamongthe swarm- peers while providinghigh chunk availability.Thealgorithm takes advantageofallresourcesfor efficient video sharingwithoutoverloading specific nodes. The server can guaranteetheavailabilityofthe video, even if the numberofonline users inaswarmissmall.

Inthisexperiment,we randomly selected 5per-node overlaysand chose aclient ineach overlay. Weleteach source nodehave 30videos in5interests.A client initiallyhas interests.Inevery simulationcycle,each client receives aprefix fromitssource node and chooses [1-4]videos to watch. Iftheclientchooses avideo notin itscurrentinterests, the video’s interestisaddedtothe client’s interestlist and itjoinsinthe interest-cluster of this interest and receives the pushedprefix of videos in this interestin Social Tube and NetTube.The averagevalue of the prefetchingaccuracies of the 5clients versusthe number of watchedvideos ofaclient over time. The figure illustrates that as the numberof watched videos increases, the prefetching accuracyof SocialTube and NetTubeincreases.This is because inSocialTube and NetTube,asaclient watches more videos, it joins in more interest-clusters and receives more prefixes, and thus itsprefetchingaccuracy increases.Again, Net Tube generateslower prefetching accuracy than SocialTube due to the same reason. The prefetchingaccuracyofPA-VoD and randomisnot affected bythenumberofwatchedvideos asthey donot have interestclusters. Also,they produce low prefetching accuracydue to the same reasonsas explainedbefore.

4.CONCLUSION

Video sharingisan increasinglypopularapplicationinOSNs.However,theclient/serverarchitecture deployed bycurrentvideo sharingsystemsinOSNs costsa large amount of resources (i.e. money, server storage) for the service providerand lacks scalability. Meanwhile, because ofthe privacyconstraintsinOSNs, the current peerassisted Video-on-Demand (VoD)techniques are suboptimalifnotentirelyapplicabletothevideosharing inOSNs.Inthispaper,wecrawled video watching trace data inoneofthelargest online socialnetwork websites Facebook, from Jul. 2007 toAug. 2010 andexplored the users’ video viewingpatterns.We foundthat in a user’sviewer group,25%viewers watchedall videos of the user drivenbysocial relationship,and the viewing pattern of the remainingnodes is drivenby interest. Basedonthe observed socialand interest relationship in video watchingactivities,weproposeSocial Tube, which providesefficient P2P-assisted video sharing services. Extensive simulationresultsshow thatSocialTube can providealowvideo startup delay and low server traffic demand. WealsoimplementedaprototypeinPlanetLabtoevaluatethe performanceofSocial Tube. The experimentalresults from the prototypefurtherconfirm the efficiency ofSocialTube.

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