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A Novel Caching Strategy in Video-on-Demand (VoD) Peer-to-Peer (P2P) Networks Based on Complex Network Theory

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Abstract

The popularity of video-on-demand (VoD) streaming has grown dramatically over the World Wide Web. Most users in VoD P2P networks have to wait a long time in order to access their requesting videos. Therefore, reducing waiting time to access videos is the main challenge for VoD P2P networks. In this paper, we propose a novel algorithm for caching video based on peers' priority and video's popularity distribution. The proposed mechanism has been evaluated on two different kinds of topology, Erdos-Renyi Model and Barabasi-Albert Model. It's necessary to mention that scale-free topologies are much more similar to P2P networks like Internet; so it's closer to reality much more. However, decreasing waiting time is more tangible in them too. The results demonstrate that how our caching mechanism can reduce delay, improve bandwidth consumption, and decrease transport costs. Finally we came to the conclusion that increasing networks' size and videos' chunks has led to decrease much more delay by using proposed algorithm.

Keywords: *Video-on-Demand, Caching, Video Popularity, Peer-to-Peer Topology, Complex Network Theory*

1. Introduction

Nowadays, live and video on demand streaming in P2P networks is the most popular media applications over the internet. These systems reduce the load on the server and provide a scalable content distribution. P2P systems are distributed systems consisting of nodes interconnected with each other, able to self-organize into network topologies in order to share resources like content, bandwidth, CPU cycles and storage. VoD systems provide multimedia services offering more flexibility and convenience to users by allowing them to watch any kind of video at any point in time.

P2P-VoD systems are capable of delivering the requested video and responsible for providing continuous multimedia visualization. These systems need to accommodate a large number of users watching the same video asynchronously, watching different parts of the same video at any given time. To make this collaboration possible, users need to contribute with a small amount of storage. Therefore, issues such as service scheduling, replication strategies should considered.

Huge amount of monitored traffic in P2P networks is due to video transmission; this issue is because of two main problems. Firstly, bandwidth requirements for video delivery is too much; secondly, routing videos from responder to requester take a long time that leads to people pass their requests up. So, reducing waiting time is another challenges in P2P networks. In addition, peer's capacity has limitation and only small number of videos can be stored on each peer at any moment. Therefore, proposing a new strategy which can cache videos properly is beneficial and aligned with the main purpose of our study. Our ultimate goal in this paper is reducing delay in receiving videos, decreasing traffic in P2P networks (like Internet), and effective usage of bandwidth capacity of peers .

The rest of our paper is organized in 5 parts as follows. Section 2 introduces some related works. Our methodology is explained in section 3. Then we come to the simulation in section 4 and finally the paper is finished by concluding the paper and proposing some future expectations.

2. Related Works

Generally all previous studies can be classified in two category: the first researches consider video popularity in VoD networks on various database and during different times [1-14] and the second group study how to cache videos in P2P networks [15-36] and we will consider them here.

At first, Hongliang Yu et.al [11], [12] in 2006 declared that video popularity matched the Zipf distribution better than predicted using the "fetch-at-most-once" model. Lei Guo et.al [1], [14] analyzed a wide variety of media workload on the internet. The workloads were collected from both the client side and server side in web, VoD, P2P, and live streaming environments. They found that the reference ranks of media objects in all sixteen workloads follow the Stretched Exponential (SE) distribution. In addition, they mentioned that Zipf-Mandelbrot and Parabolic fractal models are only accountable for a small number of workloads, while SE fits all .

Phillipa Gill et.al in 2007 [8] discovered that request arrivals can be modelled by a modified Poisson distribution, and video popularity follows the Zipf distribution in YouTube. In this regard, Kuan-Ta Chen et.al [4], [5] proposed User Satisfaction Index (USI) based on Cox Regression model. After that in 2011, a new general evaluation model[2]was developed in order to estimate user satisfaction in video streaming based on Cox Regression model; afterwards, Anders Brodersen et.al [3] provided useful information about YouTube video popularity: 1) about 50 percent of videos have more than 70 percent of their total views in a single country 2) when the fraction of socially-generated views grows larger than 20 percent, the videos experience a more focused popularity in fewer regions 3) video popularity expands and withdraws back .

Studies on YouTube caused that Salvatore Scellato et.al [7] in 2011 interested in distributing content in Twitter and they declare that social cascades are likely to spread on geographically local distances. Another studies [10] indicated that one of video's category is popular in each time; for example entertainments are more popular in weekends while scientific subjects are attractive during workdays of the week. Besides, popularity have been grown based on Rich-get-Richer pattern. Meeyoung Cha et.al [13] focused on YouTube and Daum videos. They presented that the correlation coefficient between views of videos after one day and after two days were 0.8793 and 0.9367 respectively. In one of the international conference in France in 2012 [6] Sasho et.al expressed that popularity of the content items obeys the Zipf-Mandelbrot distribution which is a generalized form of Zipf distribution and includes the shifting constant q in order to characterize the behaviour of the clients for not repeating requests of already seen content items. This opinion is in line with Jeffry's et.al view [9] that Zipf-like distribution characterize the user access of the top YouTube and Truveo search videos.

As a result, we observe that the coefficient of determination of the fitting result in each workload, R^2, is very close to one for all workloads in SE distribution. In addition, for workloads with raw data accesses, X^2 tests are conducted to check the goodness of fits.

From video caching point of view, many literatures consider this subject. The first group decreased response time by concentrating on peers' cooperation [15-20]. Cai et al. [15] just notice to video popularity and cache videos based on it. It dynamically groups the participating hosts which enforces overhead to system. One of the challenging part in caching video is its NP-Complete computational problem that studies face with it [17]. Jie et al. in 2011 [16] design resource allocation mechanism with awareness of inter-ISP traffic but this pattern is not available at any time. Centralized information about bandwidth and availability for cache replacement is another matter that emerge [18].Besides, single optimal solutions of each caching node may not result in wholly optimal solution [19] that should be noticed as well.

The Second group of literature focused on cache replacement policy based on video's weight [21-23]. Though weighted cache replacement is only based on weighting videos that arrange to replace. The next category used probabilistic model for caching [24], [25]. Although they need large amount of logs to extract a meaningful pattern and likewise how to collect logs is challenging topic.

Finally, the other category take care to video popularity for storing and replacement in servers [26-30]. They also have some problems; for instance, they didn't consider the effect of popularity dynamics on caching performance [26] or Gramatikov et al. [28] utilize tree-structure and it trailed tree structures problems.

Case studies [31] also survey useful information about video caching and their issues. Besides, some researches has been proposed video caching approach by developing a predictive component [32-34], using cloud computing [35], and applying Multiple Description Coding (MDC) method [36].However, none of them attend to node's attributes for caching and distributing video streams and this important issue is the start point of our study.

3. Methodology

A lot of research has already been done on the architectural design issues of P2P-VoD systems; Ghosh et al. [37] presents a survey on approaches which address some existing design issues and introduces some popular P2P-VoD streaming systems which use tree and mesh-based overlays. VoD systems need to accommodate a large number of users watching the same video asynchronously and this is a very challenging design situation for tree-based P2P systems. So, mesh-based structure is much better and we use this type of architecture here.

Table 1. Main Complex Networks Metrics for video streaming

	Complex Network Metrics	**Formula**
1	Degree Centrality	$D_i = \sum_{j=1}^{n} A_{ij}$ A_{ij} : *Matrix of Adjancency*
2	Eigenvector Centrality	$x'_i = \sum_j A_{ij} x_j$ X'_i : *Centrality of each vertex*
3	Authorities	
4	Hubs	
5	Closeness Centrality	$l_i = \frac{1}{n-1} \sum_{j\ (\neq i)} d_{ij}$ d_{ij} : *shortest path between i& j* $C_i = \frac{1}{l_i} = \frac{n}{\sum_j d_{ij}}$ *n : number of nodes*
6	Betweeness Centrality	n_{st}^{i} : *# of shortest path pass i from source to destination* g_{st} : *total # of shortest path from source to destination*
7	Clustering Coefficient	$C = \frac{(NumberofTriangles) * 3}{NumberofConnectedTriples}$
8	Structural Balance	…
9	Homophiles / Assortativity	$\sum_{edges(i,j)} \delta(c_i, c_j) = \frac{1}{2} \sum_{ij} A_{ij}\ \delta(c_i, c_j)$ C_i : *Type of vertex I* C_j : *Type of vertex j*

In our caching algorithm, following methodology is processed:

I. In P2P topologies, each node has a value that specified its' strength in video distributing. Thus, significant complex network metrics which has impact on video streaming is chosen.

II. Since the selected metrics have not the same influence on video distribution, their coefficient should be calculated. Two procedures has been followed out that both of them represent the same results:
   a. Using Correlation Coefficient
   b. Measuring the slope of each factor on video streaming speed

   So, NID (Node Importance Degree) is acquired.

III. NID is assigned as a weight to each node and NID distribution is found as well (Possion distribution).

IV. SE distribution is validated for video popularity model because of its goodness in fitting for all workloads.

V. By employing video popularity model and NID distribution, we found that caching popular contents on main peers leads to decrease network traffic and bandwidth requirements for serving video files.

These five steps are explained in detail in two following subsections: the first two steps in part one and the other three steps in part two.

3.1 Estimating Node Importance Degree

Initially, we assign a weight to each peer in P2P topologies that represent its quality and distinctive attribute for spreading video in that topology. For this reason, some valuable metrics are gathered [38] based on complex network basics (Table 1).

Some of these criteria are important for peer's position in VoD-P2P network; since they have not same weight in topologies, we assign a coefficient to each of them. So, Node Importance Degree (NID) can be expressed as follows:

$$\mathrm{NID} = \alpha_1 \mathrm{DC} + \alpha_2 \mathrm{EC} + \alpha_3 \mathrm{CLC} + \alpha_4 \mathrm{BC} + \alpha_5 \mathrm{CC} \tag{1}$$

Where DC, EC, CLC, BC, and CC stands for Degree Centrality, Eigenvector Centrality, Closeness Centrality, Betweens Centrality, and Clustering Coefficient respectively. Factors α_i $i \in \{1,2,..,5\}$ determine magnitude of each metric in NID. In general, these factors are not equal to each other and should be calculated as well.

In order to determine the influence of each mentioned metric on spreading, two methodologies have been wielded. In the first method, correlation coefficient was used which is the degree that indicates two sets how much are related to each other and is defined in Equation 2. We want to find that each considered metric how much can influence on video streaming.

$$r = \frac{n\left[\sum(X_i.Y_i)\right] - \left(\sum X_i\right)\left(\sum Y_i\right)}{\sqrt{\left[n\left(\sum X_i^2\right) - \left(\sum X_i\right)^2\right]\left[n\left(\sum Y_i^2\right) - \left(\sum Y_i\right)^2\right]}} \tag{2}$$

Where X_i is ith element of each metric set (for example Degree Centrality, Clustering Coefficient, etc.) and Y_i is the number of required steps to spread video in topology for ith corresponding metric. The correlation values are measured and listed in Table 2.

Table 2.Influence factor of each metric

Metrics	Correlation (R)	R^2
Degree Centrality	-0.4491	0.2017
Eigenvector Centrality	-0.6408	0.4106
Closeness Centrality	-0.9230	0.8519
Betweeness Centrality	-0.3617	0.1308
Clustering Coefficient	+0.4628	0.2142

Based on Correlation Coefficient in Table 2, NID is defined as follows:

$$\mathrm{NID} = 0.2\ \mathrm{DC} + 0.41\ \mathrm{EC} + 0.85\ \mathrm{ClC} + 0.13\ \mathrm{BC} - 0.22\ \mathrm{CC} \tag{3}$$

In second approach, for ascertaining how much the spread of streaming has been affected by peer's position, various P2P topologies with regard to different metrics' quality were formed and metrics' influences have been determined. Figure 1 is presented each metrics' impact factor for video streaming.

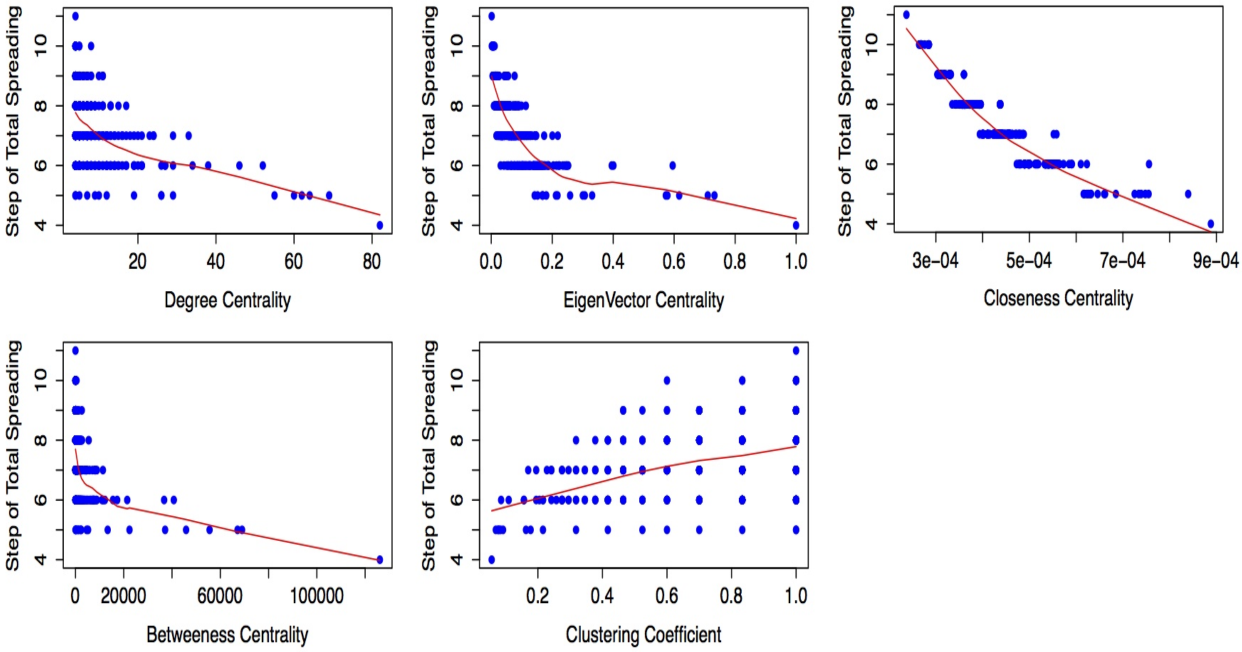

Figure 1: correlation of number of steps to video streaming based on (a) Degree Centrality (b)Eigenvector Centrality (c)Closeness Centrality (d)Betweens Centrality (e) Clustering Coefficient

Implementation results have confirmed the calculated influence factors in Table 2; for instance, all metrics shown in Figure 1 except Clustering Coefficient have negative slope against delay (number of steps to spread video). This point has been presented in calculating correlation in Table 2 previously. In the other word, we can conclude that all mentioned metrics except clustering coefficient could help to video streaming's speed and this conclusion is confirmed by sign of correlation in Table 2. Therefore both methods presented the same results.

3.2 Caching Videos based on NID

First, we should consider that how NID distribution is changed in networks. For this purpose, random topologies were formed and the NID criteria were calculated for each nodes in topologies; then their distribution were determined as well. It's significant to know that the same outcome is obtained from all random topologies (Figure 2).

As shown in Figure 2, NID distribution is conformed Possion distribution. Besides, to evaluate the SE distribution fit in video popularity, Guo et al. [14] computed the coefficient of determination of the fitting result of each workload, R^2. As reported, R^2 is very close to one for all workloads. In addition, for workloads with raw data accesses, X^2 tests are conducted to check the goodness of fits. Consequently, the SE fits are accepted while Zipf-like fits are rejected for video popularity distribution.

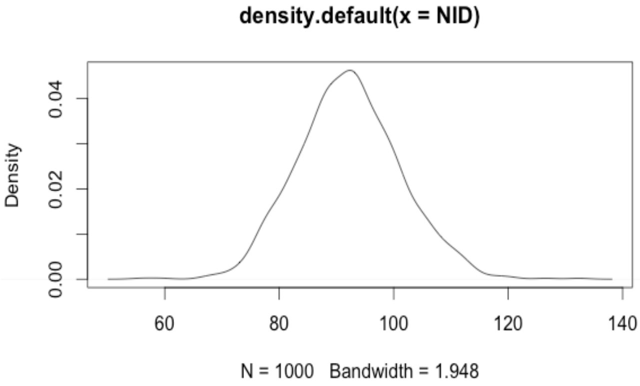

Figure 2: NID distribution in networks

Stretched Exponential (SE) distribution has two parameters: one of them well characterizes the media file sizes, the other well characterizes the aging of media accesses. Video popularity distribution and peer's characteristic indicates that caching the popular contents on precious peers has the potential to decrease network traffic and bandwidth requirements for serving video files.

In this regard, one hundred different topologies have been established (fifty with Erdos-Renyi algorithm and fifty with Barabasi-Albert algorithm). The general procedure for all topologies is as follows. First, for all nodes in topologies, NID has been measured based on their metrics, then videos are cached on them accordingly. The caching pattern is such that newcomer videos because of their high popularity are stored in nodes with higher NID value. In this way, at each moment we can collect delay in networks and submit that each requester how much should wait to access its desired video.

4. Implementation Results

Considered topologies in both approaches (proposed and random schemes) have one thousand nodes and caching capacity in all nodes, for simplicity and without loss of generality, is such that in each time one video can be stored in them. Delay has been measured based on applicants' waiting time to receive the first video chunk from responder node.

Table 3. Comparison of Average Delay between Proposed and Random caching scheme

Average Delay in 50 Topologies with Erdos-Renyi Model	
Proposed Algorithm	Random Distribution
975	978
Average Delay in 50 Topologies with Barabasi-Albert Model	
Proposed Algorithm	Random Distribution
1495	1526

Proposed algorithm has been compared with random distribution in both network models, Erdos-Renyi Model and Barabasi-Albert Model, for 50 different topologies and average delay is submitted in Table 3 in terms of milliseconds.

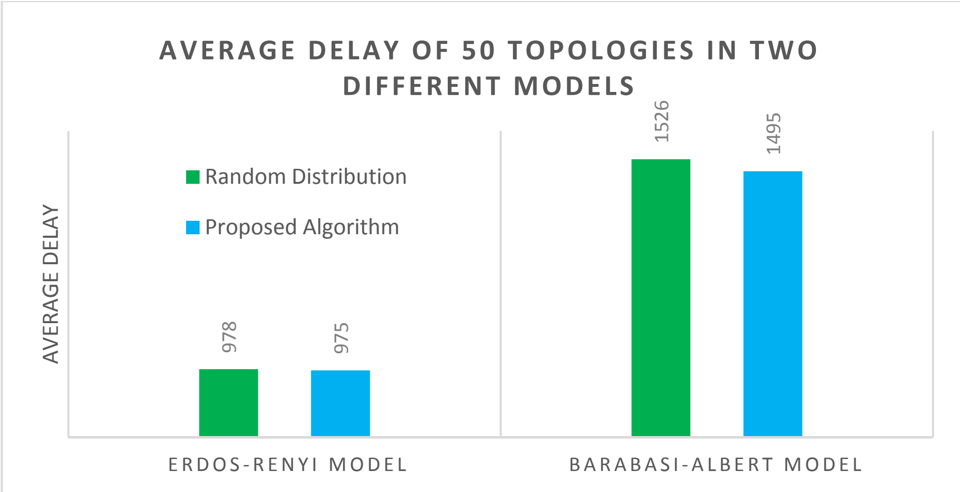

Figure 3: Comparison of Average Delay in two different network models

As shown in Figure 3, delay is decreased 31ms in scale-free networks by using proposed algorithm against random one. It's necessary to mention that scale-free topologies are much more similar to P2P networks like Internet; so it's closer to reality much more. In fifty different executions, delay was likewise registered for scale-free topologies (Figure 4).

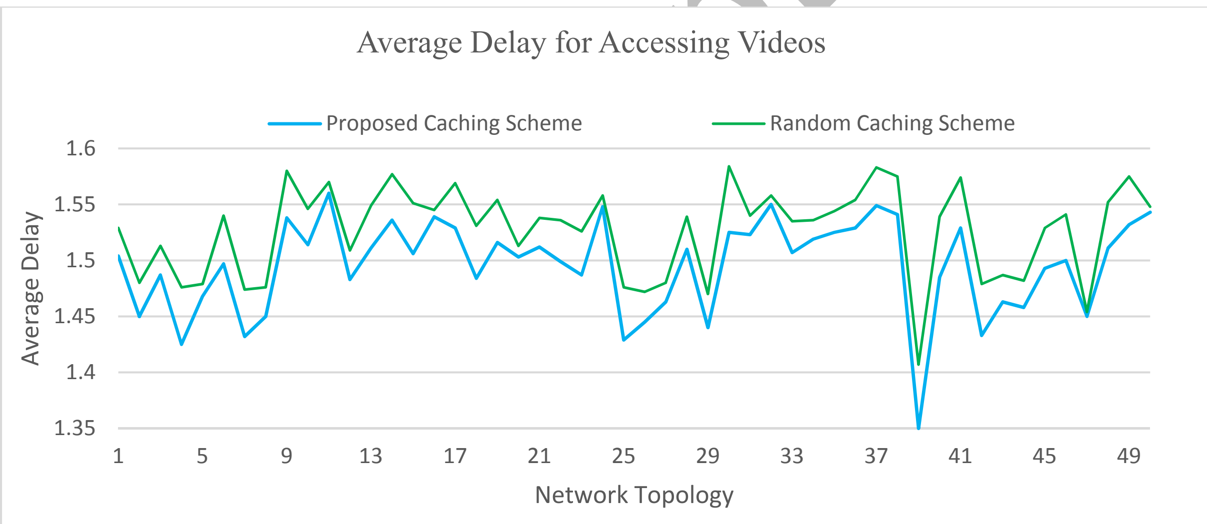

Figure 4: Comparison of Average Delay of Proposed and Random caching scheme in Scale-free networks

In the real world applications, videos have several chunks. It's Important to note that since each node received all chunks of one video with the same delay; it's obvious that if one video with one chunk is received with X millisecond delay then the other video with k chunks will be received with $k * X$ milliseconds for both approaches (proposed algorithm and random one). This differences shows that little improvement in receiving video with one chunk leads to great variation (k times) for videos with several chunks. Consequently, if networks have been observed for certain period of time, total delay for watching videos with more chunks would have been much less in proposed algorithm in comparison with random one. In addition, the real world network looks like scale-free models which their diameter grows slower than LnN [39]. As our proposed algorithm depends on node's position, so increasing networks' size changes the diameter negligibly (for large *N*), but enhances the chance of finding video chunks in neighbours' cache proportionally. As a result, increasing videos' chunks and networks' size is shown the importance of our proposed approach much better.

5. Conclusion & Future Works

In this paper, first we considered changes in the popularity of video during the time. Then by practical experiments on node's priority, we find that node's importance degree distribution follow Possion distribution in various topologies. After that by mapping these two achievements, we concluded that if videos with high popularity are stored on nodes with superior priority then total average delay has been decreased. The result of the experiments on one hundred different random and scale-free networks is confirmed the obtained hypothetical .

Finally, we came to the conclusion that increasing networks' size and videos' chunks has led to decrease much more delay by using proposed algorithm against random one. Since requester in networks like Internet with millions of nodes may ignore their request when faced with high delay, the importance of our proposed algorithm is appeared as well .

The next research challenge for authors is how to replace videos' chunks in peers' cache in order to keeping the appropriate performances of proposed method. Besides, we intend to investigate the performance of proposed algorithm on practical data like YouTube's videos.

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References

[1] Guo, L., et al., Does internet media traffic really follow Zipf-like distribution?, in Proceedings of the 2007 ACM SIGMETRICS international conference on Measurement and modeling of computer systems. 2007, ACM: San Diego, California, USA. p. 359-360.

[2] Qiu, F. and Y. Cui. A quantitative study of user satisfaction in online video streaming. in IEEE Consumer Communications and Networking Conference. 2011.

[3] Brodersen, A., S. Scellato, and M. Wattenhofer, YouTube around the world: geographic popularity of videos, in Proceedings of the 21st international conference on World Wide Web. 2012, ACM: Lyon, France. p. 241-250.

[4] Chen, K.-T., et al., Quantifying Skype user satisfaction, in Proceedings of the 2006 conference on Applications, technologies, architectures, and protocols for computer communications. 2006, ACM: Pisa, Italy. p. 399-410.

[5] Chen, K.-T., et al., Quantifying Skype user satisfaction. SIGCOMM Comput. Commun. Rev., 2006. 36(4): p. 399-410.

[6] Sasho Gramatikov, F.J., Juli´an Cabrera, and Narciso Garc´ia, Popularity Based Distribution Schemes for P2P Assisted Streaming of VoD Contents, in The Fourth International Conferences on Advances in Multimedia (MMEDIA). 2012: France. p. 14-9.

[7] Scellato, S., et al., Track globally, deliver locally: improving content delivery networks by tracking geographic social cascades, in Proceedings of the 20th international conference on World wide web. 2011, ACM: Hyderabad, India. p. 457-466.

[8] Gill, P., et al., Youtube traffic characterization: a view from the edge, in Proceedings of the 7th ACM SIGCOMM conference on Internet measurement. 2007, ACM: San Diego, California, USA. p. 15-28.

[9] Sarhan, J.R.O.N.J. Characterization of social video. in Multimedia Computing and Networking. 2009. San Jose, CA.

[10] Szabo, G. and B.A. Huberman, Predicting the popularity of online content. Commun. ACM, 2010. 53(8): p. 80-88.

[11] Yu, H., et al., Understanding user behavior in large-scale video-on-demand systems, in Proceedings of the 1st ACM SIGOPS/EuroSys European Conference on Computer Systems 2006. 2006, ACM: Leuven, Belgium. p. 333-344.

[12] Yu, H., et al., Understanding user behavior in large-scale video-on-demand systems. SIGOPS Oper. Syst. Rev., 2006. 40(4): p. 333-344.

[13] Cha, M., et al., Analyzing the video popularity characteristics of large-scale user generated content systems. IEEE/ACM Trans. Netw., 2009. 17(5): p. 1357-1370.

[14] Guo, L., et al., The stretched exponential distribution of internet media access patterns, in Proceedings of the twenty-seventh ACM symposium on Principles of distributed computing. 2008, ACM: Toronto, Canada. p. 283-294.

[15] Cai, Y., Z. Chen, and W. Tavanapong, Caching collaboration and cache allocation in peer-to-peer video systems. Multimedia Tools Appl., 2008. 37(2): p. 117-134.

[16] Jie, D., et al. On the efficiency of collaborative caching in ISP-aware P2P networks. in INFOCOM, 2011 Proceedings IEEE. 2011.

[17] Romero, P., et al., Mathematical Analysis of caching policies and cooperation in YouTube-like services. Electronic Notes in Discrete Mathematics, 2013. 41(0): p. 221-228.

[18] Jeon, W.J.N., Klara, Cooperative Caching for Multimedia Streaming in Overlay Networks, in UIUCDCS-R-2004-2501. 2004.

[19] Mo Zhou, B.J., Kunpeng Han, Hongsheng Xi. A Cooperative Hybrid Caching Strategy for P2P Mobile Network. in Proceedings of the 2nd International Symposium on Computer, Communication, Control and Automation (ISCCCA-13). 2013. Atlantis Press, Paris, France.

[20] Z. Yin, H.J.D., DHT Based Collaborative Multimedia Streaming and Caching Service, in In Proc. of the IEEE International Region 10 Conference (TENCON 2005). November 2005.

[21] S.P. Ponnusamy, E.K., Cache Optimization on Hot-Point Proxy Caching Using Weighted-Rank Cache Replacement Policy. ETRI Journal, 2013. 35(4): p. 10.

[22] Hsu, T.-H. and Y.-H. Li, A weighted segment-based caching algorithm for video streaming objects over heterogeneous networking environments. Expert Systems with Applications, 2011. 38(4): p. 3467-3476.

[23] Hailin, X. An Efficient Caching Mechanism for Video-on-Demand Service over Peer-to-Peer Network. 2009.

[24] Tian, Y., D. Wu, and K.-W. Ng, A novel caching mechanism for peer-to-peer based media-on-demand streaming. J. Syst. Archit., 2008. 54(1-2): p. 55-69.

[25] Zheng, C., G. Shen, and S. Li, Distributed prefetching scheme for random seek support in peer-to-peer streaming applications, in Proceedings of the ACM workshop on Advances in peer-to-peer multimedia streaming. 2005, ACM: Hilton, Singapore. p. 29-38.

[26] Saleh, O., Modeling and Caching of Peer-to-Peer Traffic 2006, SIMON FRASER UNIVERSITY: SIMON FRASER UNIVERSITY.

[27] Bhattacharya, A., Y. Zhenyu, and P. Deng. Popularity Awareness in Temporal-DHT for P2P-based Media Streaming Applications. in Multimedia (ISM), 2011 IEEE International Symposium on. 2011.

[28] Sasho Gramatikov, F.J., Juliلn Cabrera, Narciso Garcيa, Popularity Based Distribution Schemes for P2P Assisted Streaming of VoD Contents, in MMEDIA 2012 : The Fourth International Conferences on Advances in Multimedia. 2012: Chamonix / Mont Blanc, France.

[29] Takaya, F. Video-Popularity-Based Caching Scheme for P2P Video-on-Demand Streaming. 2011.

[30] Wang, Q., K. Daudjee, and M.Tض .zsu, Popularity-aware prefetch in P2P range caching. Peer-to-Peer Networking and Applications, 2010. 3(2): p. 145-160.

[31] SriguruLakshmi C., G.s., Venkatachalam V., SURVEY ON CACHING AND REPLICATION ALGORITHM FOR CONTENT DISTRIBUTION IN PEER TO PEER NETWORKS. International Journal of Computer Science, Engineering & Information Technology 2013. 3(5): p. 17-32.

[32] Loeser, C., et al., Content Distribution in Heterogenous Video-on-Demand P2P Networks with ARIMA Forecasts, in Networking - ICN 2005, P. Lorenz and P. Dini, Editors. 2005, Springer Berlin Heidelberg. p. 800-809.

[33] Sharma, A., A. Bestavros, and I. Matta. dPAM: a distributed prefetching protocol for scalable asynchronous multicast in P2P systems. in INFOCOM 2005. 24th Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings IEEE. 2005.

[34] Lihang Ying, A.B., pcVOD: Internet Peer-to-Peer Video-On-Demand with Storage Caching on Peers. Knowledge Systems Institute, 2005: p. 218-223.

[35] Fangming Liu, S.S., Bo Li 0001, Baochun Li, Hao Yin, and Sanli Li., Novasky: Cinematic-quality VoD in a P2P storage cloud. INFOCOM, IEEE, 2011: p. 936-944.

[36] LAN, J.-W.D.S.-Y., Quality-Adaptive Proxy Caching for Peer-to-Peer Video Streaming Using Multiple Description Coding. Journal of Information Science & Engineering 2009. 25(3): p. 687-701.

[37] Debjani Ghosh, Payas Rajan, Mayank Pandey, "Advanced Computing, Networking and Informatics-Volume 2", Wireless Networks and Security Proceedings of the Second International Conference on Advanced Computing, Networking and Informatics (ICACNI-2014), Springer International Publishing, 2014.

[38] Newman, M., Networks: An Introduction. 2010: Oxford University Press, Inc. 720 .

[39] Posfai Marton, Musella Gabriele, Martino Mauro, Sinatra Roberta, Husseini Amal, Hoevel Philipp, "Network Science", Chapter 5, "http://barabasilab.neu.edu/networksciencebook."