A Latent Social Approach to YouTube Popularity Prediction
Amandianeze O Nwana, Salman Avestimehr, and Tsuhan Chen
School of Electrical and Computer Engineering
Cornell University
Ithaca, New York 14853
Email: aon3@cornell.edu, {avestimehr, tsuhan}@ece.cornell.edu

Abstract—Current works on Information Centric Networking assume the spectrum of caching strategies under the Least Recently/Frequently Used (LRFU) scheme as the de-facto standard, due to the ease of implementation and easier analysis of such strategies. In this paper we predict the popularity distribution of YouTube videos within a campus network. We explore two broad approaches in predicting the popularity of videos in the network: consensus approaches based on aggregate behavior in the network, and social approaches based on the information diffusion over an implicit network. We measure the performance of our approaches under a simple caching framework by picking the $k$ most popular videos according to our predicted distribution and calculating the hit rate on the cache. We develop our approach by first incorporating video inter-arrival time (based on the power-law distribution governing the transmission time between two receivers of the same message in scale-free networks) to the baseline (LRFU), then combining with an information diffusion model over the inferred latent social graph that governs diffusion of videos in the network.

Contributions: We believe we are the first to propose predicting the popularity distribution by taking into account the diffusion of these videos in the network. We incorporate diffusion in two ways, first by using the inter-arrival time between requests for the same video for prediction, and then by using a virus propagation model over the latent social graph to model the spread of the videos between users. Because our approach is trace-driven, this social graph is latent. That is, we don’t have explicit friendship information as found on sites such as Facebook. Instead, we infer the (directed) edge weights between users in the graph, which are interpreted as the transmission/sharing probability between two users. An example of a social graph is seen in Fig.1.

I. INTRODUCTION

In large networks, we face the problem of having many users share the limited network resources while expecting a certain level of quality guarantee. There are many ways of addressing this issue like limiting the number of users that can access the network, scaling out the network equipment (which is expensive), or moving the content closer to the users and storing on cheap proxy caches so as to reduce end-to-end network activity.

In this work we focus on the caching perspective to this problem. The idea behind caching is that many of the requests made by the users of the network are for the same objects, so to minimize the end-to-end delay of requests in the network, the local network should store the items that are likely to be requested again, thereby eliminating the round trip delay that would have been experienced by these requests and simultaneously freeing up bandwidth and other network resources.

We demonstrate the gains that implementing cache policies while considering the social networking nature of video-on-demand requests like YouTube can give over the standard LRFU spectrum of policies. The LRFU approaches predict the popularity distribution by computing the Combined Recency and Frequency (CRF) value for each object and caching according to the scores. Computing the CRF is dependent on the weighing parameter $\gamma$, which takes on values from 0 to 1 and controls the tradeoff between recency and frequency[1], [2]. The two extremes degenerate to the Least Recently Used (LRU) when $\gamma$ is 1, and Least Frequently Used (LFU) when $\gamma$ is 0.

Fig. 1. This social graph could represent a network of 9 users, where the edges between the users represent the probability they share YouTube videos with each other.
II. RELATED WORKS

Caching is the natural framework by which we analyze and measure the effectiveness of our approaches in predicting the popularity of YouTube videos within the network versus other approaches in predicting the popularity distribution. We do this because other works such as [3–5], have explored the usefulness of caching YouTube and other online video requests and shown that there are gains to be had by using a cache. There are several differences between our work and these. In the work by Wang et al. [4], they observe and track actual friendships within social networks (Facebook, Twitter, etc) and use the patterns of propagation for the use of replicating the content in different sites, whereas in our work, we do not have access to the actual friendships derived from such social networks but instead infer unknown relationships (friendships) for predicting the popularity distribution of videos in the network under observation. In other works [3, 5], they show that the global popularity distribution from the content provider (YouTube.com) is highly uncorrelated with local popularity on local networks.

In recent years, there has been a growing interest in the field of social network analysis and its applications in real-world computational problems. A social network can be described as any network where the realized flow of objects over the links and nodes that make up the network is driven by human action or behavior. Examples include road networks, recommendation networks.

In some situations, the human actions are directly observed on application-level networks like Facebook, Twitter, and other social-media websites, where the links between the users are explicit. There are also many situations where the human-driven spread of objects in the network is not directly observed over the links. In such cases, to understand the relationship between the users, we must be able to infer from the observed network transactions, the links between these users. One example is the network between a city population and the spread of a virus over the population. In this case, the spread of an infectious virus over the population are the hidden transactions, while the observable transactions are the various records of infections by clinics, or pharmaceutical drug sales. There have been several works that have addressed the issue of latent social network (link) inference [6–9].

III. APPROACH

In our problem, at a given time \( t \in \mathbb{R} \), we observe some user \( u \in \mathcal{U}(t, w) \subseteq \mathbb{N} \) making a request, where \( \mathcal{U}(t, w) \) is the set of users at time \( t \) that made requests in the past \( w \) time units. The users are uniquely identified by the order in which they first made requests in the network. Similarly at some time \( t \), we observe a video \( v \in \mathcal{V}(t, w) \subseteq \mathbb{N} \) being requested, where \( \mathcal{V}(t, w) \) is the set of videos at time \( t \) that were requested in the past \( w \) time units. The videos are also uniquely identified by the order in which they were first requested. In the rest of this paper, for convenience of notation we represent these sets as \( \mathcal{U} \) and \( \mathcal{V} \). We represent these transactions between users and videos as a triplet \((u, v, t)\), and the set of all such triplets in a given interval as the network trace, \( T(t, w) \). Similar to the Single Cache Performance Approximation in [2], our goal is to predict for some time \( t \), in the future, the popularity distribution of these videos given a history of these triplets before time \( t \). In predicting the popularity distribution, we explore two general approaches, consensus-based approaches dependent on aggregate information in the network, and social-based approaches dependent on explicit information diffusion over nodes in the network. These approaches are evaluated under the framework of caching the \( k \) most popular videos. Given the network trace \( T \), we can calculate \( \hat{X}(t, k) \) as the k-sparse binary vector of length \(|\mathcal{V}|\), representing the \( k \) videos to be cached at time \( t \), and \( X(t) \in \mathbb{N}^{[V]} \), the vector representing the number of views each video got at time \( t \). The hit rate, \( H(\hat{X}(t, k)|T(t, w)) \), is then given as follows,

\[
H(\hat{X}(t, k)|T) = \frac{X(t) \cdot \hat{X}(t, k)}{|X(t)||X(t)|_1}
\]  

(1)

For the purpose of this paper we don’t allow partial caching of videos, and we assume all videos have the same size. Caching schemes can be divided into two steps. First, the assignment of scores to the various objects or candidates for the cache. Second, an ordering of these scores to decide which objects will end up in the cache. It is not necessary that these two steps are done separately. Some caching strategies, for example the commonly used Least Recently Used (LRU) scheme, implicitly combine the score assignment and the ordering.

We discuss the approaches we explored in the following sections.

A. Baseline

The de-facto standard for our application is caching according to the CRF values assigned to each video as shown in [2]. In [2], they come up with with a model to approximate the performance (hit rate) of the popularity distribution under the LRFU assumption independent of the actual order the videos arrive, and they demonstrate through trace-based simulations that the approximate model is a good approximate of the actual trace-based simulations using the LRFU scheme (within 5%). We compare our approaches to the approximate popularity distribution.

B. Consensus Approach

Any approach to caching videos from network traces, \( T \), that ignores the actual users/watchers of the videos is a consensus approach. Such methods rely on aggregate or average properties derived from the video request patterns, and not particularly how a video diffuses over the nodes in the network. This section discusses some consensus approaches we explored.

In improving the baseline, we will explore its deficiencies. A deficiency of the the baseline is its handling of time and recency. Since underlying the baseline distribution is the LRFU scheme, it is known that the distribution is susceptible to object staleness as seen pointed out in [10]. This is because objects can still have high CRF scores under LRFU
A deficiency of the baseline that we try to capture in this approach we model the average information diffusion networks that the propagation time can indeed growing. This is akin to a second derivative test, while the inter-arrival distribution to represent recency, we give a different angle to analyzing recency and frequency with the notion of staleness which is an achilles heel of the LRFU approach. The ordering for this approach is a sort in decreasing probability.

C. Social Approach

This approach is different from the other ones in that it considers users when predicting the popularity of a video. It predicts for each user, the probability of that user watching each video. And given those probabilities, we estimate the number of views for each video by summing over all the users, the probability each user watches that video. Before we can calculate the user-video probabilities, we must first estimate the user-user sharing/transmission probabilities. These probabilities are modelled as the edges of a diffusion graph between the users of the network.

Diffusion Model. In classical epidemiology, we can classify a given virus $v$, the population into (not necessarily disjoint) sets representing the stage each individual is in the life cycle of that virus. If they have not yet been infected at time $t$, we say they are in the Susceptible set, $S(t)$. If they have been infected and are infectious, the are in the Infectious set, $I(t)$, and if they have recovered they go into the Recovered set, $R(t)$. In this work, we consider the $S$-$I$ model, where individuals transition from being susceptible to being infectious and remain infectious once infected. The transition from $S$ to $I$ occurs in two stages, first transmission, then incubation. Before an individual can be said to be infected, they must have contracted the virus from a carrier. The difference between the contraction time of the infection and the outbreak of symptoms is the incubation time.

For this paper, the set of users is the population of individuals and the videos are the viruses. The probability that a user, $u$ gets infected by a video, $v$, at time $t$ is then the same as the probability the individual, $u \in S(t)$, contracted the infection from an already infected individual, $u' \in I(t)$, and the incubation time is the difference between $t$ and the time that $u'$ transmitted the disease to $u$. In this work we assume that as soon as user gets infected (watches a video), they immediately transmit the video to all other users not yet infected with some probability. Hence the transmission time from $u'$ to $u$ is the infection time, $\tau_{u'}^{v}$ of $u'$. Let $\chi(u', u, t)$
represent the probability that user $u'$ infects user $u$ with video $v$ at time $t$.

$$
\chi_v(u', u, t) = A_{u'u} \cdot \Delta(t - \tau_v^u) \tag{4}
$$

We learn the transmission probabilities (as an adjacency matrix $A$) under the maximum likelihood framework proposed by Myers et al in [9], and we assume that the incubation times follow a power-law distribution as diffusions in information networks have been shown to follow [11]–[16]. We use the same exponent for the power-law distribution as we do for the inter-arrival approach. The sequence/series of infections of a given video is called a cascade, and we make an independent cascade assumption, which means each video is transmitted independent of other videos.

The score for a given video is the sum, across all the users that are not yet infected, of the probability that each user is infected at the given time $t$.

$$
S_{\text{diffusion}}(v, t) = \sum_{u \in S(t)} \left[ 1 - \prod_{u' \in I(t)} \left( 1 - \chi_v(u', u, t) \right) \right] \tag{5}
$$

The ordering is a descending sort of the diffusion scores.

**D. Combined Approach**

One deficiency of the social approach is that if there is not enough data to create a complete graph based on diffusion, then we are only predicting the views for a small subset of the users in the network, which will lead to underperformance. A remedy for this is for those users that are not part of the diffusion graph, but part of the network, we estimate their probabilities from a consensus approach as previously described. Yet another observation about the social approach is that not every video watched by users that appears in the diffusion graph is necessarily fully explained through diffusion, (independent) personal tastes, influence from external sources like news sites and blogs, and so on are bound to play roles in affecting what the user watches as well. We do not attempt to fully model this phenomenon in this work, but we leave it up to a future work.

The score for the combined approach is given by,

$$
\hat{U}(v) - \text{Set of users that have not watched } v \text{ and are not in the diffusion graph}
$$

$$
S_{\text{combined}}(v, t) = S_{\text{diffusion}}(v, t) + |\hat{U}(v)| \cdot S_{\text{inter}}(v, t) \tag{6}
$$

And our rank is given by a descending sort of the combined scores.

**IV. NUMERICAL ANALYSIS AND RESULTS**

Our data is from the University of Massachussetts, Amherst, YouTube network traces described and analyzed by [3]. We utilize 120 consecutive (from Thu 03/13/2008 19:00 to Tue 03/18/2008 18:10) hours of YouTube requests from their campus network and we partition this data into a training set over the first sixty hours. The training set contains a total of 79213 requests made by 7260 unique users over 58345 unique videos. The testing set contains a total of 96568 requests made by 6383 unique users over 72528 unique videos. In the dataset, there are total of 10349 unique users and 120973 unique videos. For our experiments, we make our caching period units of length, 1 hour. For each of our these periods, we create a cache $\hat{X}(t, k)$ and as our performance metric, we look at the average hit rate over all the time periods in our testing set, for different values of $k$.

**Baseline.** As explained earlier, we rank each video in decreasing order according to its approximate popularity under the LRFU scheme it got during that time. We employ a window size of $w = 28$ for our baseline, because empirically on our training set we see that this window size gives the best average hit rate as shown in Fig. 2.

**Viralness.** For the viralness approach, we have a constraint on the lower bound for the number of requests in useful

![Fig. 2. The effect of window size on average hit rate. Window size 28 gives the best improvement.](image)

![Fig. 3. The comparison between the consensus approaches. For the smaller cache sizes, the viralness approach performs better than the other consensus approaches, and as discussed in section III-A we see that the viralness approach converges to the baseline. Over all cache sizes, we can see that the inter-arrival approach demonstrates significant improvements over the baseline.](image)
cascades from our testing set. For any video to be considered for the cache, $\tilde{X}(t, k)$, it must have at least five views ($|D_v| \geq 5$). We also add another constraint that these requests are made over at least three time periods (hours in our case), so we can sufficiently examine the growth trend over time, i.e., $I_v(1, t, w) - I_v(0, t, w) \geq 3$. Let the number of videos that fit these criteria be $n$. If $k > n$, we populate the remaining $k - n$ entries of the cache according to the order that the remaining videos occur in the baseline. For a given network trace, $n$ is fixed so as $k$ increases, the baseline and the viralness approach should converge.

We compare the results of this approach ($S_{viral}(v, 3, 8, 1, t, w)$) with the baseline (Fig.3), and we notice that for a small cache size ($k \leq 50$), we are performing better than the baseline, and after that the results converge as per intuition. On the small cache sizes, we get an improvement of about 6.1% over baseline by using the viralness approach.

**Inter-arrival Time.** For this approach we also have the constraint that the cascades used in learning the parameters for the inter-arrival distribution must be of at least length five, i.e., $|D_v| \geq 5$. This is so the averages of the inter-arrival times for the videos we will eventually be fitting to are less noisy.

We then calculate the scores as described in section III using the output of our baseline method as the input for the zipfian distribution [14], [17] used in eq.(3). We compare the result of this approach to our baseline (Fig.3) and we get on average about a 11.5% improvement in hit rate.

**Social.** To learn the incoming transmission probabilities on the training set, we must also learn power-law distribution parameters. We learn these parameters exactly as in the inter-arrival time approach. Another constraint in choosing valid cascades to learn the incoming transmission probabilities from is, $|U(D_v)| \geq 3$, where $U(D_v) = \{u : (u, v, t) \in D_v\}$. That is, not only must the cascade be at least 3 requests long, but the cascades must also have at least 3 unique users. This is an attempt to remove noise by increasing the probability that one of those views was as a result of sharing between users.

On our testing set, we relearn the adjacency matrix every ten (10) hours, and limit ourselves to only inferring from the past $w = 60$ hours of history each time we learn a new adjacency matrix. We use the algorithm described by Myers et al. in [9] with a sparsity of 300.

After these parameters and transmission probabilities are learned, we proceed to calculate the future scores of the video for each of the periods in our testing set. For each hour, we consider as prediction history all the requests that were made in the last $w = 16$ hours. We calculate the score using the function described in section III-C with the appropriate adjacency matrix.

Because of the constraints on valid cascades, we find that on average only about 40% of the users in the network are used for inference, which implies only 40% of the nodes in the graph are in a connected component and the others are just isolated nodes. This ultimately leads to under-performance (Fig.4) since for about 60% of the users we can make no estimation of the probability it views a given video. So in order to guage the usefulness of this approach, we also run it on an augmented dataset (Fig.5) where only users in the connected component are in the dataset ($\tilde{F} = \bigcup_{v \in D_v, |U(D_v)| \geq 3} D_v$).

**Combined.** As previously noted in section III-D it is unlikely that even in a connected graph, the volume of videos watched will be completely accounted for by diffusions over the graph. In [18], Myers et al., showed that only about 71% of information volume on twitter could be accounted for by network diffusions. To that end, on our data we performed
an experiment to figure the best weighting (ranging from 0% to 100% in steps of 10) between the social scores and the inter-arrival scores, and, corroborating the conclusion of [18], it came out to be 70% from social and 30% from inter-arrival. We also analyze the performance of the combined approach under the full data, and under just the connected component. Under the full dataset, we see an improvement of 13.2% from the baseline to the combined (Fig.7), and under just the connected components, our improvement rises to 21.1% (Fig.6).

We also compare the performance of the combined to the

\begin{table}[h]
\centering
\caption{Summary of Results on All Users}
\begin{tabular}{|l|l|l|}
\hline
Method A & Method B & % improvement \\
\hline
Baseline & Viralness (small cache) & 6.2 \\
Baseline & Inter-Arrival & 11.6 \\
Baseline & Combined & 13.2 \\
Inter-Arrival & Combined & 1.6 \\
\hline
\end{tabular}
\end{table}

\begin{table}[h]
\centering
\caption{Summary of Results on Connected Users}
\begin{tabular}{|l|l|l|}
\hline
Method A & Method B & % improvement \\
\hline
Baseline & Inter-Arrival & 15.6 \\
Baseline & Combined & 21.1 \\
Inter-Arrival & Combined & 4.9 \\
\hline
\end{tabular}
\end{table}

inter-arrival approach. From our experiments we see that the combination of social and inter-arrival gives an improvement of 1.6% over inter-arrival on this full dataset (Fig[7], and 4.8% when only users from the connected component are used(Fig[6]).

From our results, we see that for the social approach to give considerable gain, it is imperative that the underlying structure be a connected graph, and not a graph with mostly isolated vertices. We have also seen that the combination of the social approach with a consensus approach (inter-arrival) generally outperforms any of the individual approaches. This is because on this dataset, and as we suspect on most social networks, neither diffusion, nor consensus can fully explain the request patterns of the users in the network. Users tend to have their own preferences, and are also influenced by different external media like the news, or blogs, and such behavior has been studied by Myers et al. in [18], where they show that only about 71% of information volume on twitter can be attributed to network diffusion.

V. ROBUSTNESS AND COMPLEXITY

Our algorithms described in section III have some free parameters that are application and data specific. Although, for our application, we did not exhaustively search the parameter space for the optimal choice of these parameters, we chose our parameters based on what we believe to be reasonable assumptions. For example, our choices of what cascades to use to perform the inference was made under the assumption that cascades of shorter lengths could lead to over-fitting our model to what might be noise, hence we choose only cascades of some minimum length (elaborated on in section IV). We leave the analysis of the performance of our algorithms under varying (exhaustively) parameter settings up for future work. On the run-time of the social approach, as noted by Myers et al. in [9], the columns of the adjacency matrix can be inferred independently of each other which leads to opportunity for massive parallelization. In our experiments, each column took on average 3 seconds to be inferred solving the optimization problem via the KNITRO optimization software in MATLAB [19]. This means that for our network of about 4000 nodes, it takes about 16 minutes running 12 jobs simultaneously. And since we update our matrices only every 10 hours, this
seems a very reasonable cost to us. Given the adjacency matrix, computing the scores for our diffusion approach takes $O(|V| \cdot |U| + |V| \log |V|)$ time, versus $O(|V| \log |V|)$ for the baseline. The first term in the complexity of the diffusion approach comes from computing for every user the probability that they watch every video (which is the expected amount of each video transmitted to each user). The logarithmic term comes from the sorting of the scores. For our networks, $|V| \gg |U|$, hence the complexity of the baseline and our approach are comparable.

VI. CONCLUSIONS

In this paper we have shown that by leveraging social cues inferred from the requests made by users in the network, through an estimated latent social graph over these users, we can better predict the popularity distribution of the videos being requested by the users. Our preferred method of combining the distributions resulting from the social-approach and the inter-arrival (staleness) approach is shown to outperform other approaches. This is because our model captures the idea of videos being spread like diseases over a network of users where some users are more likely to infect (and be infected by) other users, which the other approaches do not. These considerations result in a 14% improvement over the baseline.

VII. FUTURE WORK

One of the roadblocks we faced in this work is the inadequate amount of data both in terms of recency and volume, so an immediate follow up to this work is to gather more recent data on a longer scale from different network sites and verify our findings from this work. We also aim to address the issue of the robustness of the algorithms to varying of the parameters, and the performance when the uniform video size assumption is lifted. Also in terms of future directions on different approaches, we will like to explore the application of large alphabet prediction, preferential attachment graphical models, and possibly predictive sparse coding on the this problem.

VIII. ACKNOWLEDGEMENTS

This work is in part supported by Intel-Cisco-Verizon via the VAWN program.

REFERENCES

[1] D. Lee, J. Choi, J. hun Kim, S. H. Noh, S. L. Min, Y. Cho, and C. S. Kim, “Lfu: A spectrum of policies that subsamples the least recently used and least frequently used policies,” in In Proceedings of the 1999 ACM SIGMETRICS Conference on Measurement and Modeling of Computer Systems, 2001, pp. 134–143.

[2] Z. Li, G. Simon, and A. Gravey, “Caching Policies for In-Network Caching,” in ICCCN 2012: IEEE International Conference on Computer Communication Networks, IEEE, Ed., 2012.

[3] M. Zink, K. Suh, Y. Gu, and J. Kurose, “Characteristics of youtube network traffic at a campus network - measurements, models, and implications,” Comput. Netw., vol. 53, no. 4, pp. 501–514, Mar. 2009. [Online]. Available: http://dx.doi.org/10.1016/j.comnet.2008.09.022

[4] Z. Wang, L. Sun, X. Chen, W. Zhu, J. Liu, M. Chen, and S. Yang, “Propagation-based social-aware replication for social video contents,” in Proceedings of the 20th ACM international conference on Multimedia, ser. MM’12. New York, NY, USA: ACM, 2012, pp. 29–38. [Online]. Available: http://doi.acm.org/10.1145/2393347.2393359

[5] P. Gill, M. Arlitt, Z. Li, and A. Mahanti, “Youtube traffic characterization: a view from the edge,” in Proceedings of the 7th ACM SIGCOMM conference on Internet measurement, ser. IM ’07. New York, NY, USA: ACM, 2007, pp. 15–28. [Online]. Available: http://doi.acm.org/10.1145/1298306.1298310

[6] D. Liben-Nowell and J. Kleinberg, “The link prediction problem for social networks,” in Proceedings of the twelfth international conference on Information and knowledge management, ser. CIKM ’03. New York, NY, USA: ACM, 2003, pp. 556–559. [Online]. Available: http://doi.acm.org/10.1145/956863.956872

[7] M. De Choudhury, W. A. Mason, J. M. Hofman, and D. J. Watts, “Inferring relevant social networks from interpersonal communication,” in Proceedings of the 19th international conference on World wide web, ser. WWW ’10. New York, NY, USA: ACM, 2010, pp. 301–310. [Online]. Available: http://doi.acm.org/10.1145/1772690.1772722

[8] M. Gomez-Rodriguez, J. Leskovec, and A. Krause, “Inferring networks of diffusion and influence,” CoRR, vol. abs/1006.0234, 2010.

[9] S. A. Myers and J. Leskovec, “On the convexity of latent social network inference,” in NIPS, 2010, pp. 1741–1749. [Online]. Available: http://books.nips.cc/papers/files/nips23/NIPS2010_1257.pdf

[10] E. J. Oneil, P. E. Oneill, and G. Weikum, “The lru-k page replacement algorithm for database disk buffering,” in In Proc. ACM SIGMOD International Conference on Management of Data, Washington, D.C, 1993, pp. 297–306.

[11] M. Mitzenmacher, “A brief history of generative models for power law and lognormal distributions,” Internet Mathematics, vol. 1, pp. 226–251.

[12] M. E. J. Newman, “Clustering and preferential attachment in growing networks,” Phys. Rev. E, 2001.

[13] A.-L. Barabási and R. Albert, “Emergence of scaling in random networks,” Science, vol. 286, no. 5439, pp. 509–512, 1999. [Online]. Available: http://www.sciencemag.org/content/286/5439/509.abstract

[14] “Zap’s law,” http://en.wikipedia.org/wiki/Zap’s_law & accessed: 03/11/2013.

[15] T. Mihaljev, L. de Arcangelis, and H. J. Herrmann, “Inter-arrival times of message propagation on directed networks,” CoRR, vol. abs/1011.0630, 2010.

[16] A. Capocci, A. Baldassarri, V. D. P. Servedio, and V. Loreto, “Statistical properties of inter-arrival times distribution in social tagging systems,” CoRR, vol. abs/1210.2752, 2012.

[17] H. Yu, D. Zheng, B. Y. Zhao, and W. Zheng, “Understanding user behavior in large-scale video-on-demand systems,” in Proceedings of the 1st ACM SIGOPS/EuroSys European Conference on Computer Systems 2006, ser. EuroSys ’06. New York, NY, USA: ACM, 2006, pp. 333–344. [Online]. Available: http://doi.acm.org/10.1145/1217935.1217968

[18] S. A. Myers, C. Zhu, and J. Leskovec, “Information diffusion and external influence in networks,” in Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining, ser. KDD ’12. New York, NY, USA: ACM, 2012, pp. 33–41. [Online]. Available: http://doi.acm.org/10.1145/2339530.2339540

[19] “Knitr optimization software,” http://www.ziena.com/mallab/knitr. html, accessed: 07/23/2013.