

Challenged Content Delivery Network: Eliminating the Digital Divide

Hua-Jun Hong¹, Shu-Ting Wang¹, Chih-Pin Tan¹, Tarek El-Ganainy²,
Khaled A. Harras³, Cheng-Hsin Hsu¹, and Mohamed Hefeeda²

¹Department of Computer Science, National Tsing Hua University, Taiwan

²Qatar Computing Research Institute, HBKU, Qatar

³School of Computer Science, Carnegie Mellon University, Qatar

ABSTRACT

We present a complete system, called Challenged Content Delivery Network (CCDN), to efficiently deliver multimedia content to mobile users who live in developing countries, rural areas, or over-populated cities with no or weak network infrastructure. These mobile users do not have always-on Internet access. We demo our CCDN, implemented on a Linux server, Raspberry Pi proxies, and Android phones from three aspects: multimedia, networking, and machine learning tools. We propose multiple optimization algorithm modules that compute personalized distribution plans, and maximize the overall user experience. CCDN allows people living in area with challenged networks access to multimedia content, like news reports, using mobile devices, such as smartphones. This in turn will help in eliminating the digital divide, which refers to information inequality to persons with different Internet accessing abilities.

Categories and Subject Descriptors: H.3 [Information Storage and Retrieval]: Systems and Software

Keywords: Multimedia; Challenged Networks; Content Distribution; Mobile Devices; Offline Access

1. INTRODUCTION

Using mobile devices to watch online multimedia content is getting increasingly popular. However, in developing countries, rural areas, or over-populated cities, many mobile users do not have Internet access. For instance, only 15% of mobile users have mobile Internet access in Africa [1], because of weak or non-existing network infrastructure. Therefore, people in these areas have little chance to access online multimedia content, such as news, advertisements, and movies. That is, they suffer from *digital divide* from other parts of the world. Digital divide refers to information inequality to persons with different Internet accessing abilities.

This work was partially supported by the Ministry of Science and Technology of Taiwan, #102-2221-E-007-062-MY3.

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the Owner/Author(s). Copyright is held by the owner/author(s).

MM'15, October 26–30, 2015, Brisbane, Australia.

ACM 978-1-4503-3459-4/15/10.

DOI: <http://dx.doi.org/10.1145/2733373.2807970>.

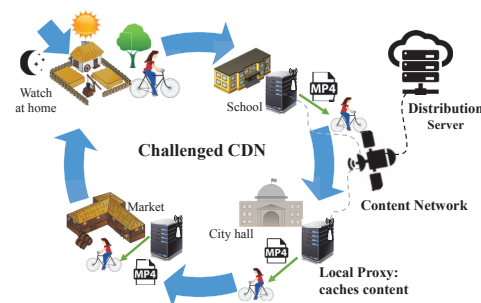


Figure 1: How CCDN helps people who suffer from digital divide.

ties. Fig. 1 shows one day of Amy who does not have Internet access at home. Online multimedia content providers cannot efficiently deliver content to Amy even after hiring Content Delivery Network (CDN) providers, because traditional CDNs take end-to-end connectivity as granted. On the other hand, Amy's mobile device is not always isolated from the Internet. Amy may run into other people and WiFi access points in crowded places, such as schools, city halls, and markets.

In this demo, we present the CCDN system for: (i) mobile users without stable Internet access to prefetch multimedia content, and (ii) service providers to deliver their multimedia content to more people. Our CCDN system consists of several entities: a *distribution server*, several *local proxies*, and many *mobile clients*. Local proxies are intelligent WiFi access points with storage spaces, which are deployed at crowded places. Local proxies retrieve online multimedia content from a distribution server over the Internet, and send it to near-by users running our mobile app over WiFi. The crux of our proposed CCDN is to make decisions on *when and which online content to transfer to which mobile client in order to achieve the highest overall user experience*. We refer to such decisions as *distribution plans*, which are periodically computed on the distribution server using a carefully designed algorithm. Several multimedia, networking, and machine learning tools are leveraged to derive the distribution plans. The plans are sent to local proxies, which relay the plans to mobile clients. The mobile clients follow their plans to download multimedia content.

2. CHALLENGED CDN: OUR SOLUTION

Fig 2 depicts the system architecture of our CCDN. The distribution planning algorithm guides mobile devices to intelligently and automatically download multimedia content:

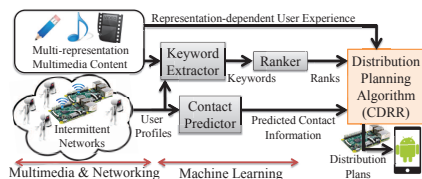


Figure 2: The system architecture of our CCDN.

(i) at the best time, (ii) with the highest viewing probability, and (iii) from the best sender. Specifically, we propose an efficient algorithm, Contact-Driven Round Robin (CDRR), which: (i) uses less resources (energy, disk, and network) to send content leading to higher user experience, (ii) sends more content to users with more chances to spread it out, and (iii) receives content from users with less chances to relay it to others. Several supporting components are described in the following.

Multi-representation multimedia content. A multimedia content may have three representations: article, audio, and video. The video can be further transcoded to different resolutions. Different representations of the same multimedia content give different user experience improvement which typically follows a decreasing function. For example, when a mobile user first downloads an article, the user will have significant user experience improvement. In contrast, moving from medium- to high-resolution video only leads to little improvement. Moreover, different users have diverse interests, and won't view uninterested content. We extract keywords of multimedia content and user interests to create personalized ranks. Multi-representation helps CCDN to gracefully adapt to diverse and dynamic environments.

User profiles in challenged networks. We deploy local proxies and leverage contacts to disseminate multimedia content over intermittent networks. In the mobile client, we keep track of user profiles, including clicked multimedia content and contact information. Contact information consists of trajectory, contact duration, and throughput of each contact. These historical user profiles are processed for the inputs of CDRR algorithm.

Machine learning modules. CCDN employs three machine learning modules: keyword extractor, ranker, and contact predictor. The keyword extractor, implementing LDA [2], is responsible for extracting the keywords of online content and user-clicked (interested) content. The ranker uses the keywords to compute per-user ranks using some ranking tools, such as LambdaMART [3]. The contact predictor estimates the contact information of mobile users in the future using popular algorithms, such as trajectory pattern [4]. CCDN provides a modularized platform for testing machine learning algorithms.

3. DEMONSTRATIONS

We design experiments to demonstrate our CCDN from three aspects: multi-representation multimedia content, intermittent networks, and matching user interests. As illustrated in Fig 3, we setup a testbed composed of Android phones running our mobile client, a Raspberry Pi running the local proxy, and a laptop running the distribution server. In this demo, the distribution server crawls daily news reports. However, CCDN also works for other types of content. Details on the experiments are given below.

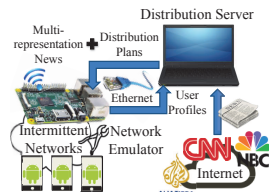


Figure 3: The setup of the demonstrations.

Multi-representation multimedia content. Sending different representations allow us to distribute more news reports under limited resources, such as network bandwidth. We install network emulator on the local proxy to throttle the available bandwidth so as to mimic challenged networks. We will show that only very few news reports can be distributed without multi-representation content.

Intermittent networks. To show the robustness of our CCDN under challenged networks, we deploy our system in a rural area, and collect contact traces. We use the traces to drive the network emulator and local proxy so as to recreate a challenged network. In particular, once we reach the first contact in the trace, we enable the WiFi interface of a local proxy, and configure the network emulator to the measured throughput in the trace. Our mobile client will associate with the local proxy and download news reports. We follow the trace, and turn off the WiFi interface on the local proxy to emulate the disconnection. We turn on the WiFi interface once contact starts, and configure the network emulator following the trace. These steps are repeated until we finish the whole trace. The mobile client will download news reports whenever the WiFi interface is on.

Matching interests. Different users have different user interests on different types of news reports. We leverage user profiles to estimate user interests and compute per-user ranks of each news report. We will demonstrate that CCDN distributes different news reports to mobile users with diverse user interests. Moreover, a mobile user tends to receive better representations for more interested news reports.

4. CONCLUSION

We presented a complete CCDN system for multimedia content delivery in challenged networks. The current multimedia content providers, such as CNN, YouTube, and Al Jazeera, provide mobile apps that offer fresh online multimedia content. However, most apps require always-on Internet access, and thus they do not work for people with challenged networks. Some of them provide offline access, which requires users to manually download favorite multimedia content, which is tedious. Hence, we believe that the proposed CCDN will help service providers to deliver more content to more users in a cost-effective way.

References

- [1] How do we accelerate Internet access in Africa? <http://tinyurl.com/q9ksjwg>, 2013.
- [2] D. Blei, A. Ng, and M. Jordan. Latent dirichlet allocation. *Journal of Machine Learning Research*, 3:993–1022, 2003.
- [3] C. Burges. From ranknet to LambdaRank to LambdaMART: An overview. Technical report, Microsoft Research, 2010.
- [4] A. Monreale, F. Pinelli, R. Trasarti, and F. Giannotti. Wherenext: A location predictor on trajectory pattern mining. In *Proc. of ACM Conference on Knowledge Discovery and Data Mining (KDD'09)*, 2009.