Optimal Distributed Caching for Mobile Peer-to-Peer Content Distribution

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***Abstract*—Mobile P2P content distribution is a promising solution to offload overwhelming growing mobile data traffic and improve the end-user experience. We study optimal distributed caching problem for mobile peer-to-peer data dissemination that leverages local cache of mobile nodes and their mobility. The problem accounts for finding the assignment of proportion of nodes to forward a set of data channels so as to maximize the global performance. As the key assumption that facilitates the analysis, we derive a close-form approximation between dissemination time of a data channel and proportion of nodes forwarding that channel. We show optimal distributed caching problem is equivalent to optimization of aggregate dissemination time over all channels whose solution can be obtained by convex optimization. Simulations based on real user mobility trace show that optimal distributed caching outperforms other data caching heuristics, especially when the number of channels is large or when the cache size is small.**

I. INTRODUCTION

Mobile users are interested in receiving data and services available in their vicinity, or interested in sharing user-generated multimedia content with other users. Even if 3G/4G cellular networks in principle can provides ubiquitous mobile Internet, they may become not scalable when user-generated content and video sharing service becomes popular, e.g., the uplink of cellular networks can easily become saturated when user-uploaded video service becomes popular. Also, 3/4G cellular networks can be less cost-effective in providing such mobile broadcast multimedia services.

Mobile Peer-to-Peer system (M-P2P) aims at providing a scalable and cost-effective wireless content distribution, especially in a user-deployed wireless network [1]. It can also efficiently offload operator's cellular network and improve the end users experience [2]. One example of M-P2P system is 7DS [3]. It explores opportunistic mobile node in contact, short-range peer-to-peer wireless connectivity (e.g., Bluetooth or Wi-Fi), and local cache of mobile devices. It can provide much larger network and service capacity than legacy centralized infrastructure network [4]. Furthermore, it is a cost-effective solution for providing roaming users in the urban area with multimedia services [5] and for the users in rural area where the legacy Internet provision is too cost [6]. M-P2P would be more suitable for applications with loose delay constraints and high data rate requirements, in which intermittent connectivity is expected and tolerated by the users. M-P2P enables mobile devices to form unstructured mobile peer-to-peer networks, dynamically self-organize and communicate in a peer-to-peer fashion. Mobile nodes that are in the transmission range of each other can communicate with their peers directly. To communicate with peers outside the transmission range, information are spread in a store-carry-forward fashion: source node disseminate the content to all its encounter nodes, encounters nodes relay the content until they meet the final destinations, i.e., a set of nodes interested in receiving the content.

We propose a practical optimal distributed caching framework for designing large-scale M-P2P system. A data channel is an abstraction for various information feeds that generate content continuously over time with some rate. For example, a channel can be a podcast feed, or profile page of an online social network application (e.g., Facebook or Twitter). We treat optimal distributed caching as a resource allocation problem, where the objective is to find allocation of proportion of mobile nodes that help disseminating each public interested channel (besides their own subscribed channels) so as to achieve optimal global system welfare. The incentive of nodes cooperation is the 'Win-Win' strategy that all mobile nodes cooperatively disseminate public interested data for their mutual benefit.

Our contributions are two-folds.

- Firstly, as a key assumption of our work, we derive a close-form approximation of channel dissemination time as a function of proportions of nodes which forwards that channel. As one key enhancement to my previous model [7], it captures two key characteristics of M-P2P system: 1) only limited data can be exchanged per node contact; 2) 'homogeneous' random-mixing and 'heterogeneous' node contact pattern.
- Secondly, we associate a utility function to each data channel with respect to their dissemination time. We show optimal distributed caching problem is equivalent to finding the assignment of fraction of nodes forward a given channel that maximizes the aggregate utility over all individual channels. The solution can be obtained by convex optimization. For the practical implementation, channel forwarder optimization is typically processed centrally at each Macro cellular Base Station (BS) that keeps track of mobile nodes in its coverage cell. To enable the channel assignment, each BS estimates dissemination time/utility function of each data channel on a regular basis to track the dynamics of mobile nodes mobility.

In previous work [7], authors propose a distributed Metropolis-Hasting (MH) algorithm for optimal distributed caching in a pure user-deployed network scenario. It requires online estimation of utility function in a distributed way. In contrast, here we consider an M-P2P system that is centralized controlled by a mobile operator who can track the mobile nodes and estimate the utility function in a centralized way.

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Periodically, the centralized optimizer at each BS assigns the fraction of mobile nodes to forward each data channel, based on its measurement data of mobile nodes in the cell.

In [8], authors propose several reputation-based heuristics for data forwarding and caching in ad-hoc podcast network.

II. SYSTEM MODEL OF M-P2P SYSTEM

We study M-P2P system consists of N mobile nodes, participating in the mobile peer-to-peer dissemination of J information channels. We denote with *U* and *J* the sets of users and channels respectively. Every node u has a list S(u) of subscribed channels. We assume that S(u) is fixed and pre-determined for every u. Furthermore, every node caches a number of helped channels for public interests, i.e., help disseminating a set of channels for others. When two nodes meet, they update their cache contents as follow: when nodes u and u' meet, u gets from u' the content that is newer at u' for the channels that u either subscribes to or helps, and vice-versa. We assume nodes only associate pair-wise even if there could be several neighboring nodes within proximity. The aim is to maximize the amount of data transferred during each node meeting, since each node meeting can be very short. Node pulls the new content from its peer only based on its own interests, rather than new content being pushed from peers. Node firstly updates the content of its subscribed channels from its peer, and then updates the content of its helped channels from its peer. The purpose is to give priority to user subscribed channels over helped channels. We do not account for the overhead of establishing contacts and negotiating content updates. We assume that once in a while a node gets direct contact to the Internet and downloads fresh content for the subscribed or helped channels. The key factors for M-P2P system performance are the distributed caching public interested channels in mobile nodes, disconnection times of mobile nodes, and node contact duration, where the latter two are nature behavior and cannot be controlled.

At any given point in time, we call *x* the global system configuration, defined by

$x_{u,j} = 1 \Leftrightarrow$ node u subscribes to or helps channel j.

Let *H*(*u; x*) be the set of channels helped by node *u* when the configuration is *x* and let *F*(*u; x*) be the set of forwarded channels, i.e.,

$$F(u, x) = H(u, x) \cup S(u), u \in U$$

We believe in most scenarios the number of information channels is so large that the users are only able to either subscribes or help disseminating a limited subset of channels due to the resource constraints of the mobile device, i.e., limited cache size or battery. We assume that every node u has a maximum cache capacity C_u. We also assume that the cache of every node is always full (by caching subscribed and public-interested channels). To simplify the analysis, we count the maximum cache size in the number of channels and assume that each channel only contains one entry or chunk [1] of the same size. We assume that $C_u \geq |S(u)|$ i.e. every node can always store all the subscribed channels while it is only willing to cache limited public interested channels to help their disseminations. Thus, the configuration is constrained by:

$|F(u,x)| \leq C_u$ for all $u \in U$, $|\bullet|$ *defines cardinality of a set*

The problem is then to find a configuration *x* that satisfies these constraints and maximizes some appropriate performance objective defined in following sections. We use the following notation:

$s_j =$ Proportion of nodes that subscribe channel j

$f_j(x) =$ Proportion of nodes that forward channel j

$$= \frac{1}{N}\sum_{u \in U} x_{u,j}$$

Without loss of generality, we assume that channels are labeled in non-increasing order with respect to their subscription popularity, i.e., $s_1 \geq \ldots \geq s_J$ for $\vec{s} = (s_1, \ldots, s_j)$ and the same for $\vec{f} = (f_j, \ldots, f_J)$.

Finally, we assume that each node have a dedicated channel to access centralized global knowledge database of M-P2P system, i.e., each node u has the knowledge of *N,* S(u) and H(u, x) for node u; s_j, $f_j(x)$ for channel j etc.

III. CHANNEL DISSEMINATION TIME

In this section, we model the mobile peer-to-peer data dissemination by epidemic theory [9]. In particular, we derive the close-form asymptotic expression of channel dissemination time as a function of proportion of forwarding nodes. The assumptions here are that limited data can be exchanged per node contact and node contacts are in random mixing environment. Our model captures the following characteristic of the system:

- Limited data exchanged per node contact. It is likely that two moving nodes only meet for a short-lived duration during which they can only synchronize limited amount of data. Limited data exchanged could also be due to the limited battery for cooperative peer-to-peer content sharing, as nodes are only willing to contribute a limited power for helping distribute data of public interest
- Homogeneous random-mixing and Heterogeneous node meeting. Under random-mixing assumption, each node meets other nodes with the sane frequency. It is a common approximation of data dissemination process in the literature. Also our model can capture the none-random mixing node meetings by dividing nodes into communities based on their geographic locations, each of which has its own node contact pattern.

We consider a channel j and set the time origin to the time at which the most recent update was created by the source. We assume the configuration x is fixed and omit it from the notation in this section. Let $\sigma_j(t)$ be the proportion of the subscribers to channel j that at time t have received a piece that was originated by the source in the time interval [0, t]. Let

[1] One entry is one data chunk. One information channel can have multiple entries. For the simplicity of the analysis, we assume each channel has one entry in our model. Thus cache size is in number of channels or chunks

$\phi_j(t)$ be the proportion of the forwarders of channel j (both subscribers and helpers) that has received a piece made available by the source in the time interval [0, t]. According to epidemic theory [9], for each channel j, nodes can be classified into four types: susceptible subscriber of channel j, infected subscriber of channel j, susceptible helper of channel j, and infected helper of channel j. Also, as forwarders of channel j is consist of subscribers and helpers of channel j, susceptible forwarder of channel j = (susceptible subscriber + susceptible helper) of channel j. The dynamics of the system can be described by the following system of Ordinary Differential Equations (ODEs):

$$\frac{d}{dt}\sigma_j(t) = P_1 \bullet ((s_j - \sigma_j(t)) \bullet \lambda_j + (s_j - \sigma_j(t)) \bullet \eta \bullet \phi_j(t)) \quad (1)$$

$$\frac{d}{dt}\phi_j(t) = P_2 \bullet ((f_j - \phi_j(t)) \bullet \lambda_j + (f_j - \phi_j(t)) \bullet \eta \bullet \phi_j(t)) \quad (2)$$

Where λ_j is the contact rate between a node and an infrastructure (e.g., WLAN Access Point) that is able to deliver channel j, and η is the contact rate between nodes. These equations correspond to the "random node mixing" assumption and are asymptotically valid when N is large. We assume infrastructure can deliver the content of all J channels. Eqs (1) (2) are explained respectively as:

$\frac{d}{dt}\sigma_j(t) = P_1 \bullet (R_1 + R_2)$, where R_1 is the rate of susceptible channel j subscribers meeting the infrastructure; R_2 is the rate of susceptible subscribers channel j meeting other infected channel j forwarders.

$\frac{d}{dt}\phi_j(t) = P_2 \bullet (R_3 + R_4)$, where R_3 is the rate of susceptible channel j forwarders meeting the infrastructure; R_4 is the rate of susceptible channel j forwarders meeting other infected channel j forwarders.

For each node, we assume contact durations between any node and Access Point (AP) are statistically the same as contact duration between any pair of nodes. We add two scaling factors P_1 and P_2 into the system of ODEs to model the situations where two nodes can only exchange limited amount of data pair-wise node meeting. P_1 and P_2 are constant and have the value between 0 and 1.

To solve Eqs (1) (2), we assume the following Initial condition: $\sigma_j(0) = 0$, $\phi_j(0) = 0$

$$\frac{d\sigma_j}{d\phi_j} = \frac{s_j - \sigma_j}{f_j - \phi_j} \Rightarrow \sigma_j(t) = s_j \bullet (1 - (1 - \frac{\phi_j(t)}{f_j})^{P_1 P_2}) \quad (3)$$

Upon solving Eqs (1)(2)(3), we have the following:

$$\phi_j(t) = \frac{1}{\eta} \bullet (-\lambda_j + \frac{\lambda_j \bullet (\lambda_j + f_j \bullet \eta)}{\lambda_j + \eta \bullet f_j \bullet e^{-P_2(\eta \bullet f_j + \lambda_j) \bullet t}}) \quad (4)$$

$$\sigma_j(t) = s_j + (1 - \frac{\lambda_j \bullet (e^{(\lambda_j + \eta \bullet f_j) \bullet P_2 \bullet t})}{\lambda_j \bullet e^{(\lambda_j + \eta \bullet f_j) \bullet P_2 \bullet t} + \eta \bullet f_j})^{P_1 \bullet P_2} \bullet (1 - s_j) \quad (5)$$

Close-Form Channel Dissemination time: Say that time T_0 a chunk is issued by the source. Let T 1 be the time at which a proportion α of the subscribers have received this or a more recent chunk. We call $t_j = T_1 - T_0$ the dissemination time and take it as metric for channel j.

Define $\alpha = \frac{\sigma_j(t)}{s_j}$, $0 < \alpha < 1$ and by solving Eqs (3)(4)(5) :

$$t_j = \frac{\ln \frac{(\lambda_j + \eta \bullet f_j \bullet K)}{\lambda_j \bullet (1 - K)}}{(\lambda_j + \eta \bullet f_j) \bullet P_2}, \ K = (1 - (1 - \alpha)^{\frac{1}{P_1 \bullet P_2}}) \quad (6)$$

We show the following proposition regarding dissemination time: Proof can be found in Appendix attached to the paper.

Proposition 1: $t_j(f_j)$ ***is a monotonic non-increasing, strictly convex function of*** f_j

IV. CHANNEL DISSEMINATION TIME ON HETEROGENEOUS NODE MEETING

The above study assumes the 'homogeneous' random-mixing node meetings, i.e., each node behaves statistically the same; each node has the same probability of meeting other nodes; each node has the same probability of meeting the AP. Now we extend our model to non-random mixing environment where the node meetings are heterogeneous. We divide the area covered by the M-P2P system into *M* disjoint regions. For each region, the set of parameters of node meetings defined above are different. We assume that the pair-wise meetings times between mobile nodes within region *m* are represented by exponentially distributed random variables with mean inter-meeting time $1/\eta_m$, and the pair-wise meeting times between mobile nodes and APs are represented by exponentially distributed random variables with mean inter-meeting time $1/\lambda_m$. The time at which at which mobile nodes move from region *m* to *n* is assumed to be represented by exponentially distributed random variables with mean rat μ_{mn}. The system of ordinary differential equations for region *m* is as follows:

$$\frac{d}{dt}\sigma_j^m(t) = P_1^m \bullet ((\lambda_j^m + \eta^m \bullet \phi_j^m(t)) \bullet (s_j^m - \sigma_j^m(t)) - \sum_{\forall n \neq m} \mu_{mn} \bullet \sigma_j^m(t) + \sum_{\forall n \neq m} \mu_{nm} \bullet \sigma_j^n(t))$$

$$\frac{d}{dt}\phi_j^m(t) = P_2^m \bullet ((\lambda_j^m + \eta^m \bullet \phi_j^m(t)) \bullet (f_j^m - \phi_j^m(t)) - \sum_{\forall n \neq m} \mu_{mn} \bullet \phi_j^m(t) + \sum_{\forall n \neq m} \mu_{nm} \bullet \phi_j^n(t))$$

$\sigma_j^m(t)$ is the proportion of the subscribers to channel j that at time t have received a piece that was originated by the source in the time interval [0,t] at region *m*.

To obtain $\frac{d}{dt}\sigma_j^m(t)$, we first count the sum of the rate of susceptible subscribers of channel j meeting other infected forwarders of channel j in the region *m* and the rate of susceptible subscribers of channel j meeting the Access Points in the region *m*, and the rate at which infected subscribers of channel j move into region m from other regions in the network. We also subtract the rate at which infected subscribers of channel j move out of region *m*. Finally, the sum rate is multiplied with a factor P_1^m to model the limited data changed during a node meeting.

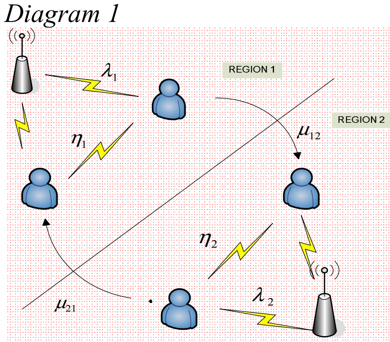
$\phi_j^m(t)$ is the proportion of the forwarders of channel j that has received a piece made available by the source in the time interval [0, t] at region *m*.

The formulation of $\frac{d}{dt}\phi_j^m(t)$ is similar to $\frac{d}{dt}\sigma_j^m(t)$.

For the simplicity of analysis, we show two regions case of heterogeneous node meetings. An example of a two region network is shown in Diagram 1. The dynamics of the system can be described by the following system of ordinary differential equations:

$$\frac{d}{dt}\sigma_j^1(t) = P_1 \bullet ((\lambda_j^1 + \eta_1 \bullet \phi_j^1(t)) \bullet (s_j^1 - \sigma_j^1(t)) - \mu_{12} \bullet \sigma_j^1(t) + \mu_{21} \bullet \sigma_j^2(t)$$
$$\frac{d}{dt}\phi_j^1(t) = P_2 \bullet ((\lambda_j^1 + \eta_1 \bullet \phi_j^1(t)) \bullet (f_j^1 - \phi_j^1(t)) - \mu_{12} \bullet \phi_j^1(t) + \mu_{21} \bullet \phi_j^2(t)$$
$$\frac{d}{dt}\sigma_j^2(t) = P_1 \bullet ((\lambda_j^2 + \eta_2 \bullet \phi_j^2(t)) \bullet (s_j^2 - \sigma_j^2(t)) - \mu_{21} \bullet \sigma_j^2(t) + \mu_{12} \bullet \sigma_j^1(t)$$
$$\frac{d}{dt}\phi_j^2(t) = P_2 \bullet ((\lambda_j^2 + \eta_2 \bullet \phi_j^2(t)) \bullet (f_j^2 - \phi_j^2(t)) - \mu_{21} \bullet \phi_j^2(t) + \mu_{12} \bullet \phi_j^1(t)$$

Diagram 1



V. Utility Optimal Allocation

We assume that for each channel there is an underlying utility function $U_j(t_j)$ that specifies the satisfaction of a subscriber for channel j with the dissemination time t_j. It is natural to assume that $U_j(t_j)$ is a non-increasing function of t_j. We will discuss later in this section some additional properties that appear natural for the utility $U_j(t_j)$ function to satisfy. We denote with $V_j(f_j) = U_j(t_j(f_j))$ the utility function for channel j with respect to the fraction of users who forward channel j. It is natural to assume that $V_j(f_j)$ is a monotonic non-decreasing function of f_j. This indeed follows, if both $U_j(t_j)$ and $t_j(f_j)$ are non-increasing functions which are rather natural assumptions.

Secondly we define the system welfare utility, i.e., when considering all channels together. We admit standard definition that the system welfare is a weighted sum of the utilities over all channels, i.e. for given positive weights

$$\vec{w} = (w_1, \ldots, w_J), \quad V(\vec{f}) = \sum_{j \in J} w_j V_j(f_j) \tag{7}$$

Two special cases are of interest, which correspond to different fairness objectives. The former is *channel centric*, in that it considers each channel as one entity, regardless of the number of subscribers. This utility is obtained by setting all the weights w_j to 1, hence we have

$$V_{CH}(\vec{f}) = \sum_{j \in J} V_j(f_j) \tag{8}$$

where V_j is a per-channel metric, for example as in Eq. (6).

The latter is *user centric* and has the weights such that w_j is proportional to the proportion of subscribers s_j, hence we consider

$$V_{US}(\vec{f}) = \sum_{j \in J} s_j V_j(f_j) \tag{9}$$

with V_j as before.

Sufficient Conditions for Concave Utility

We discuss a set of sufficient conditions that ensure that the utility $V_j(f_j)$ is a concave function of f_j. This class of utility functions ensures uniqueness of the solution to the system welfare problem that we consider below:

Proposition 2: ***Suppose (C1)*** $U_j(t_j)$ ***is a non-increasing, concave function of*** t_j ***and (C2)*** $t_j(f_j)$ ***is a convex function of*** f_j***. Then*** $V_j(f_j)$ ***is a concave function of*** f_j ***.***

Proof can be found in Appendix attached to the paper.

We pose a system welfare problem where the objective is to optimize the aggregate utility of channel dissemination times subject to the end-user capacity constraints of public cache. It is nature to assume users are only willing to limited public cache for disseminating public interested channels. Solving the system welfare problem amounts to finding an assignment of users to channels that solves *SYSTEM* problem shown in Diagram 2. Defining the system welfare utility as a sum of individual utilities is standard in the microeconomics framework of the resource allocation and was successfully applied in the contexts of wireline Internet [10]. Note that in ***SYSTEM***, w_j are positive constants that can be arbitrarily fixed. In particular, it is of interest to set w_j proportional the portion of users subscribed to channel j, i.e., s_j. In this case, the utility $V_j(\cdot)$ can be interpreted as the utility for channel j for a typical j-subscriber.

Diagram 2

SYSTEM

Maximize $$\sum_{j=1}^{J} w_j V_j\left(\frac{1}{N}\sum_{u=1}^{N} x_{u,j}\right) = \sum_{j=1}^{J} w_j V_j(s_j + h_j)$$

over $h_j \in [0, 1\text{-}s_j]$

subject to $$\sum_{j=1}^{J} h_j \le c - s$$

Here c and s are the average per node capacity and per node number of subscriptions, respectively,

$$\hat{c} = \frac{1}{N}\sum_{u=1}^{N} C_u \qquad \hat{s} = \frac{1}{N}\sum_{u=1}^{N} |S(u)|$$

In our study, we assume each node has the same cache size, then

$$\hat{c} = C_u \qquad \hat{s} = |S(u)|$$

SYSTEM is a convex optimization problem with strictly concave objective function, thus it has unique global optima. The dual problem is $\min_{\mu \ge 0} F(\mu)$ where

$$F(\mu) = \max_{h \in H} F(h, \mu)$$

$$F(h,\mu) = \sum_{j=1}^{J} w_j V_j (s_j + h_j) - \mu \left(\sum_{j=1}^{J} h_j - (\hat{c} - \hat{s})\right)$$

$$H = \{ x \in [0,1]^J : x_j \le 1 - s_j, j = 1, \ldots. J \} \qquad (10)$$

The problem (13) separates into the following optimization problems, for j = 1, . . . , J,

CHANNEL-j

$$\text{maximize} \quad w_j V_j (s_j + h_j) - \mu\, h_j$$

$$\text{over} \quad h_j \in [0,\, 1\text{-}\, s_j] \qquad (11)$$

For each j, CHANNEL-j is a convex optimization problem so there is a unique optimum solution h_j. The objective is a concave function with h_j. Let us first consider the optimization without the constraint $h_j \in [0,\ 1 - s_j]$. The necessary and sufficient optimality condition is

$$w_j V_j^{'} (s_j + h_j) = \mu \qquad (12)$$

Hence, $s_j + h_j = V_j^{'-1}(\mu / w_j) := D_j(\mu / w_j)$.

In case $h_j \in [0, 1 - s_j]$, we have that the solution to ***SYSTEM*** satisfies $h_j = D_j(\mu / w_j) - s_j$. The condition $h_j \in [0, 1 - s_j]$ can be rewritten as $s_j < D_j(\mu / w_j) < 1$.

In other cases of the unconstrained problem, we either have $h_j \le 0$ or $1 - s_j \le h_j$ and hence the solution to ***SYSTEM*** is 0 and $1 - s_j$, respectively.

To summarize, there is a unique solution to *SYSTEM* that satisfies the following:

$$h_j(\mu) = \begin{cases} 0 & D_j(\mu / w_j) \le s_j \\ D_j(\mu / w_j) - s_j & s_j < D_j(\mu / w_j) < 1) \\ 1 - s_j & 1 \le D_j(\mu / w_j) \end{cases} \qquad (13)$$

where Dj(·) is the inverse of $V_j^{'}$ (·) and μ is the solution of

$$\sum_{j=1}^{J} h_j(\mu) = \hat{c} - \hat{s} \qquad (14)$$

The solution can be interpreted as follows:

The function $D_j(x)$ can be interpreted as the demand for the forwarding capacity for channel j, given a shadow price x [10]. The shadow price for a channel j is equal to μ / w_j. If the demand by a channel is less than or equal to the forwarding capacity provided by the subscribers of this channel, then the channel gets no extra forwarding capacity. If the demand of a channel is greater than what can be supported by the system (all users forward the channel), then all users forward this channel. Otherwise, the portion of users that forward the channel is equal to the demand for this channel.

VI. PERFORMANCE EVALUATION

In this section, we present simulation results using real-world user mobility trace to demonstrate the performance of utility optimal (OPT) distributed caching allocation. We design a discrete event simulator of M-P2P system coded in C++. We employ CAM mobility trace [11] for performance evaluation. CAM is a data trace of human mobility in the area of Cambridge, UK. The CAM dataset contains information about the contacts between 36 human-carried, Bluetooth equipped devices over slightly more than 10 days. We compare OPT distributed caching allocation by *SYSTEM* with two other caching heuristics UNI and TOP as benchmarks:

UNI: Under the uniform channel selection, each user u picks a subset of (Cu − |S(u)|) channels by sampling uniformly at random without replacement from the set of channels that user u is not subscribed to, i.e., from the set of channels J\S(u).

TOP: Under the top popular channel assignment, each user u picks channels from the set of channels J\S(u) without replacement in decreasing order of the channel subscription popularity and random tie break until Cu − |S(u)| channels are picked or there are no channels left. This is a greedy scheme that favors popular channels.

We study both channel-centric Eq.(8) and user-centric system welfare Eq.(9) defined in section IV. We define the system welfare using the dissemination function $t_j(f_j)$ in Eq.(6) and letting $V_j(f_j) = -t_j(f_j)$ where $V_j(f_j)$ is a concave function of f_j (**Proposition 1,2**). To simply the analysis, both P_1 and P_2 in Eq.(6) are set to 1, i.e., two nodes only have a few data to be exchanged which can be fully synchronized in each contact duration. We also set λ_j for all channel j is 1 and η is 100 in Eq.(6), while α is set to 0.9. The summary of simulation parameters are in Table I. By solving *SYSTEM* in Eqs.(13)(14) in MATLAB, we obtain optimal helper node allocation per channel, i.e., $h_j(\mu)$ for channel j. Then we pre-select $h_j(\mu)$ proportion nodes to help disseminate channel j by uniformly random selecting from the total N nodes. For UNI and TOP heuristic, the set of nodes that help disseminate channel j are also pre-selected based on their definitions above.

We assume the channel subscription rates follow a Zipf distribution [12] with the scale parameter equal to 2/3. The S(u) for each node u is pre-generated according Zipf-distribution. We compare OPT with UNI and TOP under both various number of channels conditions and cache size conditions. For each setting of the simulation parameters, we repeat the experiment 30 times, each time injecting a message of a channel to a user picked uniformly at random from the users who are either subscribers or helpers for given channel at the beginning of the trace. We define empirical channel dissemination time for channel j is computed as the elapsed time from the moment of injecting the channel j message to the moment of 90% ($\alpha = 0.9$) channel j subscribers receiving the message. Then the mean channel dissemination time over all channels is used as performance metric to compare OPT with UNI and TOP.

TABLE I. FIXED SIMULATION PARAMETERS

Channel Dissemination Time (see Eq (6))	$P_1 = 1$, $P_2 = 1$ $\alpha = 0.9$, $\lambda_j = 1$, $\eta = 100$
Channel Popularity Distribution	Zipf with scale exponent 2/3
User mobility trace	CAM Trace [8]
Number of mobile nodes	36

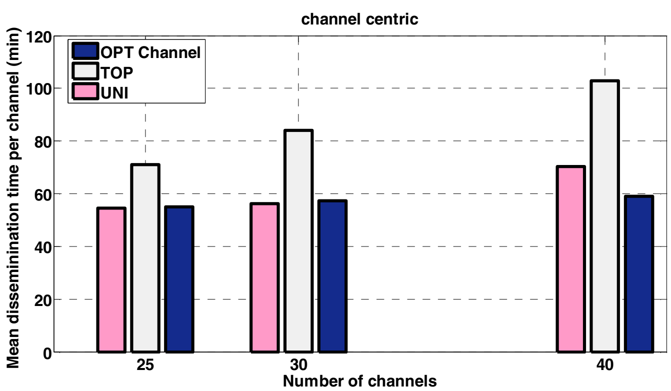


Figure 1. Channel centric welfare-OPT VS (UNI and TOP)

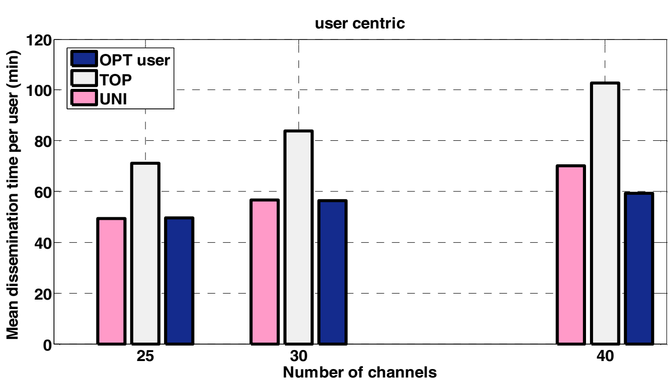


Figure 2. User centric welfare-OPT VS (UNI and TOP)

Firstly, we consider a scenario with 10 subscriptions per each user, and 10 helped channels per each user. We vary the total number of channels from 25 to 40 and compare OPT, UNI and TOP. Fig. 1 shows the mean dissemination time per channel for the channel-centric case. In the x-axis, the unit is number of channels. In the y-axis, the unit is minutes. "OPT Channel" means optimal solution by *SYSTEM* for channel-centric system welfare Eq.(8) while "OPT user" means optimal solution by SYSTEM for user-centric system welfare Eq.(9). In terms of mean dissemination time per channel, it is observed that OPT always achieve much better performance than TOP under all three number of channels conditions. OPT performs as well as UNI when the number of channel is 25 and 30 while it becomes better than UNI as the number of channel increases up to 40. Fig.2 shows the means dissemination time per channel per user for the user-centric case. We observe the same trend as Fig. 1, where OPT always performs best under three number of channels conditions while OPT brings more performance gain when the number of channels becomes large.

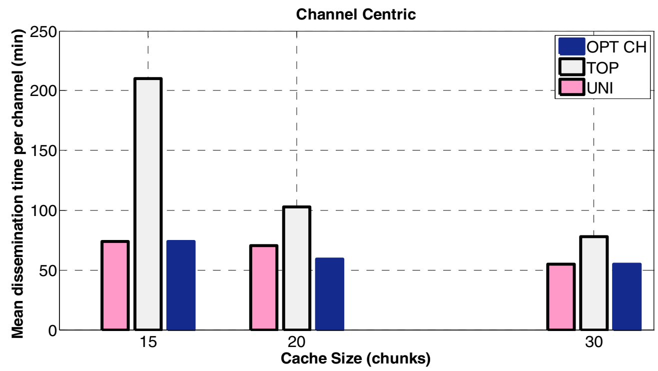


Figure 3. Channel centric welfare-OPT VS (UNI and TOP)

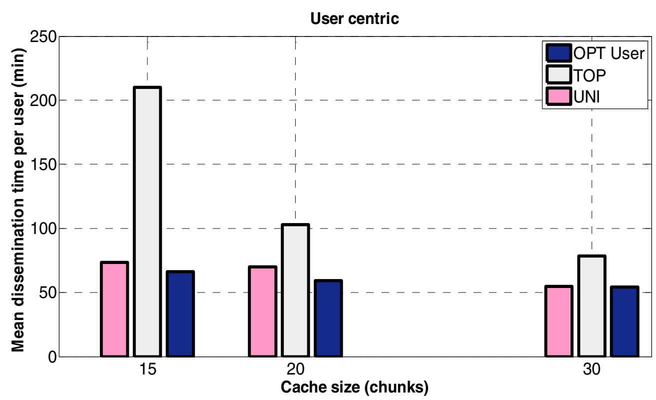


Figure 4. User centric welfare-OPT VS (UNI and TOP)

Secondly, we also compare OPT VS UNI and TOP under various cache sizes per node conditions, where the number of channels is fixed to 40. Fig. 3 shows the mean dissemination time per channel for the channel-centric case, under the cache size per node C_u is 15, 20 and 30 chunks (or channels). For every user, the cache size for subscribed channels is always 10 chunks (or channels) while the remaining cache size for helped channels varies from 5 to 20 chunks (or channels). In terms of dissemination time per channel, it is observed that OPT always achieve much better performance than TOP under three cache sizes conditions. OPT can far outperform TOP when the cache size is small, i.e., 15 chunks or channels. Also, UNI can perform as well as OPT when the cache size becomes large, e.g., from 15 to 30 chunks (or channels). Fig.4 shows the means dissemination time per channel for the user-centric case. We observe the same trend as Fig. 3, where OPT always performs best while OPT brings more performance gain when the cache size is small.

VII. CONCLUSION

We study an optimal distributed caching framework for mobile peer-to-peer data dissemination. The problem accounts to finding the assignment of proportion of nodes to help disseminating a set of information channels so as to optimize global system welfare. The key assumption in our work is that there is a relation between the channel dissemination time and the proportion of nodes forwards the given channel. We obtain this relation by using epidemic modeling. Secondly, we assign a utility to the dissemination time of each channel. We show the optimal distributed caching is equivalent to system welfare optimization problem where the objective is to optimize aggregate utilities over all individual channels. The optimal caching can be solved using centralized convex optimization. Simulation results based on real user mobility trace show that the optimal solution OPT by *SYSTEM* can significantly outperform other assignment heuristics TOP and UNI. The performance gain of OPT is mostly achieved when the number of channels is large or when the cache size is small. We also found out that, when the number of channel is small or cache size is large, UNI can be a good approximation of OPT, as it achieve almost similar performance as OPT.

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APPENDIX

A. *Proof of Proposition 1*

Let $T(f) = \eta \bullet t(f) \bullet P_2$ and $\lambda = \lambda_j / \eta$, $t(f)$ is as in Eq (6)

$$\Rightarrow \; T(f) = \frac{1}{\lambda + f} \bullet \log(a \bullet f + b) \tag{15}$$

Where $a = \frac{K}{(1-K)\bullet\lambda}$, $b = \frac{\lambda}{(1-K)\bullet\lambda}$ (16)

Taking the second order derivative of T(f), we have the following:

$$\frac{d^2}{df^2}T(f) = \frac{2}{(\lambda+f)^3}\log(a\bullet f+b) - \frac{2a}{(\lambda+f)^2}\frac{1}{af+b} - \frac{a^2}{\lambda+f}\frac{1}{(af+b)^2}$$

It follows that (d^2/df^2) $T(f)$ >0, i.e., T(f) is strictly convex, if and only if

$$\log(a\bullet f+b) - a\frac{\lambda+f}{a\bullet f+b} - \frac{1}{2}\left(a\bullet\frac{\lambda+f}{a\bullet f+b}\right)^2 > 0 \tag{17}$$

Let $x = a \bullet \frac{\lambda + f}{a\bullet f + b} \;\Rightarrow\; a\bullet f + b = \frac{b - a\lambda}{1-x}$

$\Rightarrow b - a\bullet\lambda = 1 + \frac{K}{1-K} > 1$, for 0<K<1

We can also re-write (17) as the following:

$\log\frac{b-a\lambda}{1-x} - x - \frac{1}{2}x^2 > 0$, i.e. $\frac{1-x}{b-a\lambda} < e^{-x(1+\frac{1}{2}x)}$

Given that $b - a\bullet\lambda = 1 + \frac{K}{1-K} > 1$, we could prove (17) by prove the following inequality:

$$1 - x < e^{-x(1+\frac{1}{2}x)}$$

Indeed, according to mean-value theory, we can prove (17) as the following:

$e^{-x(1+\frac{1}{2}x)} = 1 - x + \frac{1}{2}h''(x^*) > 1 - x > \frac{1-x}{b-a\lambda}$, for $0 < x^* < x$ and the readily checked property that $h''(x) > 0, for$ any x>0.

Finally, since we proved $T(f)$ is a strictly convex function of f, it means $t(f)$ in Eq (6) is also strictly convex function of f.

B. *Proof of Proposition 2*

By simple differential calculus,

$$V_j' = U_j'(t_j)t_j'(f_j)$$

$$V_j''(f_j) = U_j''(t_j)(t_j'(f_j))^2 + U_j'(t_j)t_j''(f_j)$$

From (C_1) $U_j'(t_j) \le 0$, $U_j''(t_j) \le 0$, and (C_2) $t_j''(f_j) \ge 0$, it follows $V_j''(f_j) \le 0$, i.e., $V_j(f_j)$ is a concave function of f_j