Social Groups Based Content Caching in Wireless Networks

Nimra Mustafa
LUMS University
18030049@lums.edu.pk
Imdad Ullah Khan
LUMS University
imdad.khan@lums.edu.pk
Muhammad Asad Khan
Hazara University
asadkhan@hu.edu.pk
Zartash Afzal Uzmi
LUMS University
zartash@lums.edu.pk

ABSTRACT

The unprecedented growth of wireless mobile traffic, mainly due to multimedia traffic over online social platforms has strained the resources in the mobile backhaul network. A promising approach to reduce the backhaul load is to proactively cache content at the network edge, taking into account the overlaid social network. Known caching schemes require complete knowledge of the social graph and mainly focus on one-to-one interactions forgoing the prevalent mode of content sharing among circles of ‘friends’. We propose Bingo, a proactive content caching scheme that leverages the presence of interest groups in online social networks. The mobile network operator (MNO) can choose to incrementally deploy Bingo at select network nodes (base stations, packet core, data center) based on user profiles and revenue numbers. We approximate the group memberships of users using the available user-content request logs without any prior knowledge of the overlaid social graph. Bingo can cater to the evolving nature of online social groups and file popularity distribution for making caching decisions. We use synthetically generated group structures and simulate user requests at the base station for empirical evaluation against traditional and recent caching schemes. Bingo achieves up to $30\%$ to $34\%$ gain over the best baseline.

CCS CONCEPTS
• Networks → Network algorithms.

KEYWORDS
Caching, Wireless networks, Mobile Social Networks

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1 INTRODUCTION

The rapid growth in the use of smart mobile devices over the last decade has resulted in an explosive increase in mobile data traffic. The major contributing factor is the increasing number of one-to-many transmissions in the form of multimedia messaging to groups and content posted with fans over social networks [2, 11, 15].

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resulting redundant and repetitive transmission of content [16] stresses the cellular backhaul.

Proactively caching content at the network edge and locally serving repeat requests will alleviate the wireless backhaul resource stress and also reduce user-perceived latency. Traditional web caching systems do not work as well in modern-day traffic where an enormous amount of content is created, shared, and forwarded by a large number of users. Online Social networks are often organized in the form of overlapping interest groups followers of Facebook pages, Twitter users, and members of Instagram circles. These groups or communities are characterized by their similar interests (usually requesting the same contents).

This paper proposes Bingo, a social community-based edge caching scheme. Community structure in the (logical) social network is not known to the MNO, Bingo estimates the groups from the user-request log. Bingo leverages this social locality information (contents shared with social groups) to proactively cache content at the network edge (e.g., base station). Thus, multiple members of a single social group receive the content of their mutual interest from the respective edge nodes. Bingo outperforms traditional caching schemes in terms of the cache hit ratios, thus resulting in (i) reduced usage of backhaul bandwidth, and (ii) smaller latency for end-users.

Figure 1: Users belonging to two overlapping communities $A$ and $B$ are scattered in three cells served by base stations $BS_1$, $BS_2$, and $BS_3$. Possible caching locations are at the base stations (e.g., at $BS_1$, as shown) and at the cellular core.

A practical feature of Bingo is its flexibility to be deployed incrementally at multiple levels of regional granularity, as per the business priorities of the mobile operators. An operator may choose to deploy Bingo at a single base station (e.g., a cell containing $BS_1$ in Figure 1). This will allow content caching at the base station.
For instance, if the content shared with community $A$ is cached at the BS1, it will be served locally from this edge cache to the six members of community $A$ served by BS1.

Alternately, Bingo may be deployed in the cellular packet core of a provider, allowing content caching in the core, bringing caching benefit to the members of a social community split into multiple base stations. In Figure 1, if the content destined for community $A$ is cached at the cellular packet core, then all 18 members of community $A$ across the three cells will benefit from this locality of reference. Bingo also supports a cache hierarchy by simultaneous deployment at select base stations, the packet core, and a remote data center. With hierarchical deployment, the decision engine in Bingo will cache a piece of content only at those edge nodes which may serve multiple members of the social community interested in that content. Many known caching schemes take into account the overlaid logical social network to decide Where to cache and When to cache. There also exist collaborative caching schemes using device-to-device (D2D) communication that cache content at users’ devices not just for themselves but also for their “social friends” in a tit for tat manner. These schemes however require complete knowledge of the social graph, focus on one-to-one interactions rather than content sharing among circles of friends, and/or do not adapt to quick content popularity changes.

Bingo addresses all the above concerns: it does not require knowledge of the social graph; it does not even try to estimate the social graph (respecting the security and privacy of user traffic). Instead, employing existing overlapping community detection techniques on the weighted user network modeled from the request log, Bingo approximates the community structure in the overlaid social network. For making a caching decision, Bingo considers local (instead of global) popularity of content—by measuring the interest of relevant communities. Finally, Bingo also incorporates other features of social traffic such as geographic locality (content shared among users that are geographically close by) and temporal locality (recent content is more popular) in caching decisions.

We empirically evaluate Bingo in an extensive set of experiments with varying community structures, a wide range of network densities, and file popularity distributions. All parameters used for generating synthetic test data are set to values observed in real-life data and as used in the literature. Our empirical evaluation demonstrates that Bingo achieves up to 34% gain over known edge caching schemes in terms of cache hit-ratio.

Altogether, this paper makes the following contributions:

- Methodology to estimate the (evolving) social communities based on past user requests without additional information
- An open-source prototype implementation of Bingo (including community detection, community identification, and caching decision engine) 1
- A thorough evaluation of Bingo using synthetic social groups on a broad range of parameters

The rest of the paper is organized as follows. We review existing literature in Section 2 and explain the algorithm in Section 3. We present the experimental setup in Section 4 and discuss empirical results in Section 5, concluding the paper in Section 6.

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1[https://github.com/NimrahMustafa/SocialCommunityBasedCaching.git]
that sufficient requests are available to reliably estimate the community structure and can be altered to accommodate the frequency of significant changes in the community structure. With the estimated community structure $C_k'$ in place, for each request $(u_i, f_j)$ in $D_k$, since $u_i$ may belong to many communities, we identify the community as a member of which $u_i$ has requested $f_j$ after which a caching decision for $f_j$ is made and an existing file in the cache may be removed as per the eviction policy. If cached, remaining requests by users of the community can be served locally.

**Community Detection:** To estimate the community structure, we first transform the request log into an undirected weighted graph to model a user-user network. The users form the nodes, and an edge between any pair of users is weighted by the number of common files requested by both users. Edges with weight below $\beta$ are dropped. The threshold $\beta$ can be appropriately set to reduce the likelihood of incorrect inclusion or exclusion of a user in a community, i.e., for a given period, its value should be high enough for a low likelihood of two users belonging to different communities requesting at least $\beta$ files. Then, an existing community detection algorithm can be directly run on the graph. We use a simple conductance-based algorithm [6] for community detection. Although community detection is computationally expensive, it is sufficient to periodically perform this task in the background during off-peak hours, since these communities evolve rather slowly. Bingo would cater to significant changes occurring in a period on the order of hours.

**Community Identification:** A minimum of $\xi$ requests by users for a file $f_j$ are accumulated before a community is identified, which must be among the set of common communities to which users who have all requested $f_j$ belong. The optimal value of $\xi$ can be fine-tuned depending on the overlap factor of the communities which, in many real-world social networks, is small, communities can be identified accurately in a short time, i.e., for a small value of $\xi$. We must account for users who may have individually requested $f_j$ and may not have any common communities with the other requesting users since, otherwise, the likelihood of the intersection of communities to which requesting users belongbeing empty will be higher. To this end, we sort the requesting users in descending order by the number of communities they belong to. The intersection process begins with the user belonging to the most number of communities. In each step, the intersection of the set of potentially identifiable communities is taken with the set of communities to which the next user belongs. This process stops when some minimum number of potential communities $\rho$, a configurable parameter, remain from which the largest is selected as the identified community $\chi_j$.

**Caching Decision:** The caching decision for a file $f_j$ is primarily driven by $|\chi_j|$, i.e., the number of users belonging to the identified community. We assign each requested file $f_j$ a score $s_j$ and cache the highest-scoring files. If a community is identified, $s_j = |\chi_j| - \xi$. Otherwise, $s_j = 1$. For each user who belongs to $\chi_j$ and requests $f_j$ after $\chi_j$ is identified, $s_j$ is decremented. For each cached file $f_j$, the number of requests elapsed since $f_j$ was last requested $l_j$ is used to incorporate a recency factor in the caching decision to avoid unnecessarily occupying cache space. If $f_j$ is evicted without having served all its expected requests, the number of served requests $r_j$ is temporarily retained so when $f_j$ is next cached with identified community $\chi_j$, $s_j$ is set based on $\max(|\chi_j| - r_j, 0)$ which is a higher score than $s_j$ deserves and would adversely impact caching of more deserving files. The record is deleted once the expected number of requests of $f_j$ have been served. The cache is modeled as a Min-Heap to support the eviction policy, i.e., find and delete the file with the minimum score.

**4 EXPERIMENTAL SETUP**

MSNs have two components: the social network among users and the mobile network of user requests for content. Since the ownership of these two components lies with different entities, the combination of both social and mobile data traces is limited. Due to this lack of real data, we simulate request arrivals at the base station using both synthetic and real-world community structures. Since it is well-known most social networks (Twitter, Facebook, etc.) are scale-free, we use the affiliation graph model (AGM) [14] to construct the social community structure. We chose the AGM model over other benchmark community generation models such as LFR, which generate user-user networks since a user-community bipartite membership network suffices for our purpose as we do not use the pairwise links between users. We detail the process of realistic request arrival simulation in the source code.

Users request files according to their popularity, which is sampled from the Zipf distribution, which is well known for modeling file popularity. [2] Popularity $p_j$ of a file $f_j$ is defined as $p_j = \frac{1}{j^\alpha}$, where $\alpha \geq 0$ is the steepness parameter of the popularity curve. A smaller value of $\alpha$ implies that fewer files are more popular. $F$ is a static set of $10^6$ files (effectively infinite). Parameters for community estimation and identification are set as $\beta = 3$, $\xi = 4$, and $\rho = 2$ empirically with no notable deviation from expectation with setting to other values. We evaluate the caching engine using the known community structure to avoid any bias of the community detection algorithm. Since community detection is a widely studied problem in itself, more sophisticated algorithms can be employed to improve performance.
We compare the cache hit ratio, which directly translates to the traffic volume offloaded from the backhaul links, with five baseline schemes: FIFO, LFU, LRU, MPC, and Random (RND) Caching. Since our focus is on What to cache, no meaningful comparison can be made with other state-of-the-art works which primarily focus on Where to cache. Other quality metrics such as page load times and backhaul bandwidth usage are easily derived from hit ratio when network specifications (such as link capacities) are available. The impact on the hit ratio of three key system parameters - traffic volume, cache capacity, and content popularity, is studied.

5 RESULTS AND DISCUSSION

Since a series of batches of requests is used to simulate their arrival, the traffic volume is controlled by the parameter batch size $B$ that indicates the number of currently active communities (for which users are requesting content). As expected, the hit ratio decreases for all caching schemes with an increase in traffic volume. However, Bingo maintains a significant gain over the baselines, up to 34% over the closest baseline, i.e. LRU. When traffic volume in the network is higher, a better cache hit ratio becomes more crucial to reduce response latency and backhaul load. We also observe that increasing the cache capacity $S$ increases the performance gap and thus it is more fruitful for Bingo compared to the baseline schemes.

Content popularity is controlled by the parameter $\alpha$ of the Zipf distribution. The hit ratio increases slightly for all caching schemes when $\alpha$ is increased, i.e. file popularity becomes less uniform because the same popular content is being requested more often (by more communities), more requests are served locally as compared to when fewer files were popular, i.e. more diverse content was being requested. Our experiments show that for $\alpha > 0.8$, MPC, LFU, and LRU show a drastic increase in hit ratio whereas Bingo shows a relatively smaller increase. However, such skewed distributions are not realistic and do not reflect request patterns in the real world. Bingo consistently outperforms the baselines for practical popularity distributions [2, 15].

Note that Bingo outperforms MPC, the main competitor since the number of files available is essentially infinite, and caching what more users are expected to request is better than expecting users to request only a few popular files. Furthermore, this implementation of MPC uses exactly known file popularity distribution, unlike in reality. We consider static popularity distributions since Bingo does not depend on the global popularity of the content and instead draws on the local dynamics of ‘popularity’.

6 CONCLUSION

We proposed Bingo, a proactive edge caching scheme for cellular networks that utilizes structural information of the social network. For each requested content, we identify the approximate community that maintains the maximal interest in that content. The estimated size of the community, together with the current cache status is used to make caching decisions. MNO may choose to deploy Bingo at select sites based on expected revenues. We generate user requests using synthetic communities, which simulate real-world scenarios, to empirically evaluate Bingo. We demonstrate that Bingo substantially outperforms the (more) reactive caching schemes on varying network traffic volumes and community structures.

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