Tag-Assisted Social-Aware Opportunistic Device-to-Device Sharing for Traffic Offloading in Mobile Social Networks

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Abstract

Within recent years, the service demand for rich multimedia over mobile networks has kept being soaring at a tremendous pace. To solve the critical problem of mobile traffic explosion, substantial efforts have been made from researchers to try to offload the mobile traffic from infrastructured cellular links to direct short-range communications locally among nearby users. In this article, we discuss the potential of combining users' online and offline social impacts to exploit the device-to-device (D2D) opportunistic sharing for offloading the mobile traffic. We propose *T*ag-*A*ssisted *S*ocial-*A*ware D2D sharing framework, *TASA*, with corresponding optimization models, architecture design, and communication protocols. Through extensive simulations based on real data traces, we demonstrate that TASA can offload up to 78.9% of the mobile traffic effectively.

Index Terms

Social Awareness, D2D Communication, Traffic Offloading, Online Social Networks, Mobile Social Networks.

I. INTRODUCTION

Recently, mobile networks have been supporting a growing number of multimedia services, and mobile users always download a large number of multimedia content files onto their mobile devices (e.g., smartphones). This challenge results in explosively growing of traffic load [1], which becomes one of the most severe concerns of mobile

network operators (MNOs). To effectively support the growing traffic load, the MNOs and network equipment vendors has been trying to adopt more and more sophisticated communication techniques but the efficiency of utilizing authorized radio spectrum resources is nearly reaching the theoretical cap.

One interesting observation has lifted billows of mobile industry that as indicated in [2], most of the traffic load on the Internet can be generated by duplicated downloads of the same popular contents. For instance, the top 10% of popular videos in YouTube may account for nearly 80% of all the view requests [2]. Thus the MNOs have to deliver the same video streams from the remote servers to mobile users at multiple times, which brings a huge waste of resource in MNOs' networks.

In addition to cellular communications, actually a mobile user can also obtain the content files from other users in proximity, through short-range communications such as Bluetooth and WiFi Direct. Therefore due to the fact that people are always clustered as crowds in certain areas (e.g., companies, apartments, subways, cafes), the **offloading** solution, for offloading mobile traffic to sharing among people, has a great potential to significantly reduce the cellular traffic load caused by duplicated contents, and has been attracting an increasing research interest from both academia and industry.

Until now, a number of techniques have exploited the device-to-device (D2D) sharing opportunities during intermittent encounters of mobile users for offloading the traffic into mobile social networks (MSNs) (a type of delay tolerant networks with social relations of users) [3] [4]. In MSNs, users are able to securely discover the adjacent users [13] for establishing temporary local connectivities and thus sharing already-downloaded contents with each other. It is worth mentioning that recently, 3GPP (the 3rd Generation Partnership Project) has designed D2D technique as a novel and attractive underlay to Long Term Evolution Advanced (LTE-A) networks [5], by which mobile users can use the authorized spectrum of MNOs for communicating directly without infrastructured support. For brevity, we use the term *D2D sharing* throughout this article for any kind of aforementioned local direct short-range communication techniques.

Towards such a D2D-based traffic offloading concept, one essential issue is, how to initialize the content dissemination by appropriate *users*, so called "seeds", which should be very potential ones to download the content files and to move around for sharing [3] [4]. To this regard, two challenges should be further elaborated: *1) how to model and to predict the content sharing pattern of each user over interested content regarding individual social activities and life patterns [6]? 2) how to design effective content dissemination strategy by exploiting realistic social relationships among users?*

Although there have been some related studies for social D2D sharing in MSNs, e.g., the studies in [4] and [7] which both discuss the optimality of social-aware D2D-based content dissemination by selecting initial seed users, they all define the social relations based on mobility statistics, which cannot indicate users' real social relationships. Therefore, for exploring the natural social aspect of MSNs, we observe the dramatic rise in the number of people who frequently participate in activities in the online Social Network Services (SNSs), e.g., Facebook, Twitter and Sina Weibo, where more and more popular contents are recommended and propagated widely and rapidly [8] [9]. Social relationship among SNS users has been researched intensively in the literature, and the "opinion leaders" with strong social impact always perform essential roles in spreading interesting and popular content due to the "word-of-mouth" effect [10]. We are thus motivated to combine users' social properties from SNSs and real mobility patterns, for social-aware D2D sharing and traffic offloading.

Consequently we will utilize several important properties and observations of online SNSs and offline MSNs as following:

- For quantifying and predicting the social-aware D2D sharing potentials, the **spreading impact** can be obtained from SNS behavior histories, either based on probabilistic modeling [9] [11] [12] or based on tag systems [7], and the **mobility impact** among users can be analyzed based on mobility traces [3] [4] [7].

- Studies in [6] [8] [9] have pointed out that there are often certain delays of sharing and re-sharing behaviors. This user access patterns, **access delays**, which are mostly user-dependent due to their differences of life styles, can be measured and modeled for guaranteeing the Quality of Service (QoS) during delay-tolerant D2D content sharings [8] [9].

- The **homophily** [1] and the **locality** [2] properties of user relations and interests in SNSs and MSNs indicate that users are clustered mostly by regions and interests both online and offline, and thus prove the feasibility of combining online and offline user data for facilitating social D2D sharing-based traffic offloading [3] [10].

In this article, we propose a novel framework to offload cellular traffic via *T*ag-*A*ssisted *S*ocial-*A*ware *(TASA)* opportunistic sharing by exploiting D2D communications in MSNs. TASA is based on the consideration of the **tags** of users and contents, and hence the modeling of social and mobility impacts, while the tags indicating the social ties among users can accelerate the choosing of initial seeds and the spreading procedure of contents. In addition, systems architecture and protocols of the TASA framework will be designed considering aforementioned

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[1] http://en.wikipedia.org/wiki/Homophily
[2] http://en.wikipedia.org/wiki/Locality_of_reference

issues carefully. And we will also evaluate TASA by real traces to prove its effectiveness.
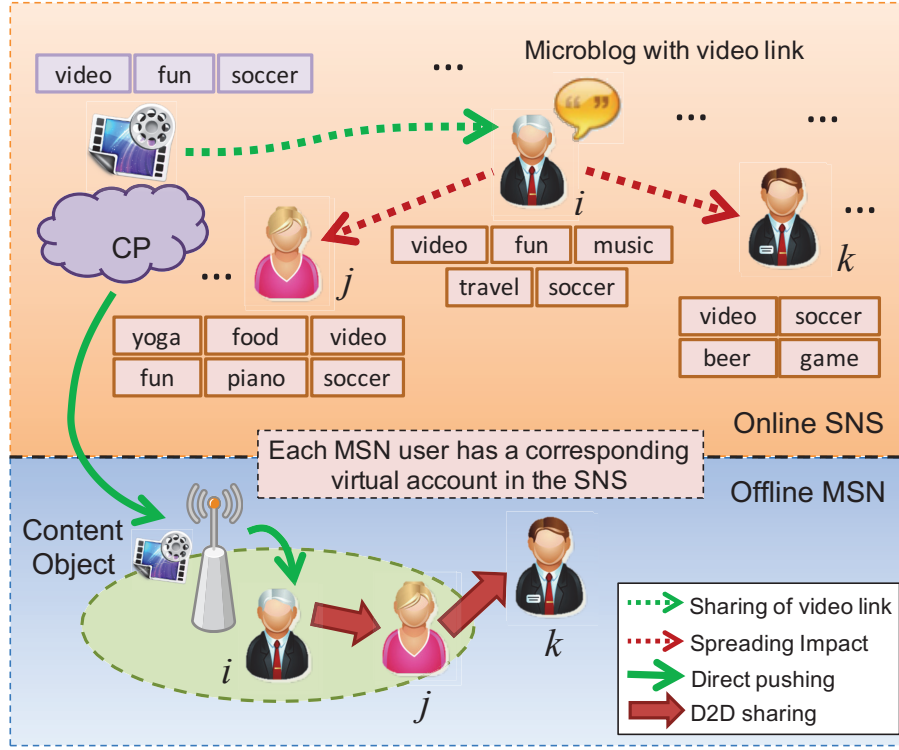
II. TASA FRAMEWORK

Fig. 1. Illustration of TASA

We illustrate the TASA framework by one typical scenario as shown in Fig. 1, where it entails both a layer of online SNS and a layer of offline MSN. Here we again declare that, the term of "online" is for the virtual accounts in the SNSs on the Internet, and the term of "offline" is about the real human-being in the physical world, i.e., MSNs, corresponding to their online accounts. We assume that in this typical scenario, there are total N mobile users, u_i, $i = 1, ..., N$, who are real persons and each has a corresponding SNS account. The dashed arrow in the online SNS layer in Fig. 1 from u_i to u_j means u_i has a direct social impact to u_j for content spreading.

Referring to the fact that many popular SNSs have tagging system (e.g., Twitter and Sinca Weibo), in TASA, contents can be assigned (either automatically or manually) by several tags, i.e., *video*, *fun*, *soccer* and so on, while users can be also characterized with certain amount of tags based on the contents that they have published, i.e., *video*, *soccer*, *beer* and *game*. Furthermore, content's tags can be interactively updated based on the tags of users that have accessed the content. The modeling of social relationships based on the tags will be detailed in Sec. III-A

For user u_i, TASA defines two online SNS factors, **the spreading impact**, I_i^S, **the social similarity** between

two users based on tags, τ_{ij}, indicating user's importance for propagating the posts, and one offline MSN factor, **the mobility impact**, I_i^M, indicating user's importance for sharing content objects (files) via encounters.

Based on above factors, what TASA tries to achieve is while the posts with the contents (i.e., posts) are being spread in the online SNS, by selecting a proper subset of users from the potential receiver group as seeds for directly pushing the real content object via cellular links, the object will be then delivered among users in the offline MSN by exploiting the social D2D sharing. We define a vector $\overrightarrow{p}$ to indicate whether TASA will push the object to any user by using the cellular link or not. For example, $p_i = 1$ means to download the content object directly to user u_i via the cellular link. Note that TASA framework is not strictly confined to the dissemination of one popular content object to all users, but can extend to apply to normal deliveries of any content object to any group of potential recipients.

From TASA's illustration in Fig. 1, u_i shares a video (link) in the online SNS with the tags of *video*, *fun* and *soccer* to u_j and u_k, while the video file is first downloaded by u_i via a cellular link and stored in u_i's phone. In the offline MSN, u_k is distant from u_i geographically, but u_j is in proximity between them. TASA analyzes that the I^S and I^M impact factors and τ similarity between u_i and u_j are very strong, so it directly let u_i's phone to share the video to u_j by D2D connectivity. TASA further detects that the impact factors and similarity between u_j and u_k via u_i are strong, although u_j and u_k are not direct friends, TASA will trigger u_j to deliver the content to u_k by D2D sharing. Apparently TASA reduces 2/3 of the cellular traffic in this simple scenario.

III. SOCIAL-AWARENESS FOR D2D SHARING: FROM ONLINE TO OFFLINE
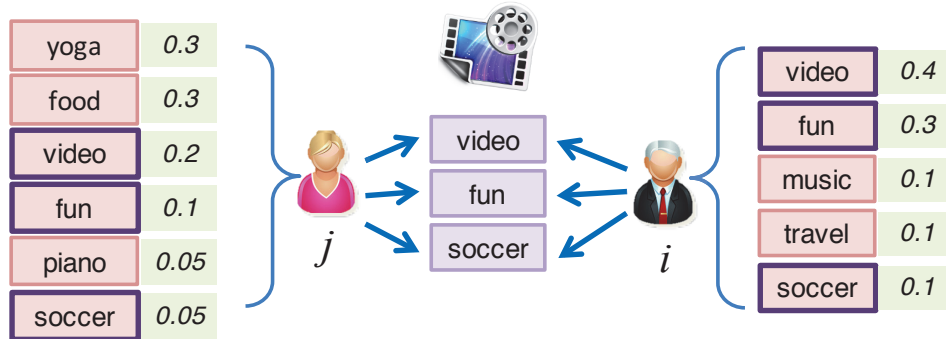
A. Online Spreading Impact

Fig. 2. Illustration of Social Tags

Tag-based impact will be quantified based on related probabilistic models [11] [12], and tags will be estimated as

a comprehensive probability from user interests. TASA generally allows a user to have various interests in different content files. As illustrated in Fig. 2, tags are with ample information to compute the similarity of two users, especially the weights of tags will be important to indicate users' preference on contents.

We hence model the tags within a fixed keyword space with size N_T to describe how the probability of user interests can be calculated. The tag profile of a user u_i is a N_T probability vector, $G_i = [g_{i1}, g_{i2}, ..., g_{iN_T}]$, where g_{ik} indicates the user weight (probability) to be interested in the kth tag. In practice, g_{ik} is used to compare the users interests in different tags. Hence, $\sum_{k=1}^{N_T} g_{ik} = 1$ for $\forall i$, and τ is calculated: $\tau_{ij} = \sum_{k=1}^{N_T} (g_{ik} \cdot g_{jk})$ Hereby, we declare the I^S of u_i to the whole base of users is: $I_i^S = \sum_{j=1, j \neq i}^{N} \tau_{ij}$. For example from Fig. 2, user u_i has *video* tag with weight 0.2, *fun* tag with weight 0.1, and *soccer* tag with weight 0.05. And then the **Social Similarity**, τ, between the two person will be calculated by: $0.2 \times 0.4 + 0.1 \times 0.3 + 0.05 \times 0.1 = 0.115$.

For obtaining the realistic tag data from SNSs, we choose one of the most popular Chinese SNSs, Sina Weibo, and we had been keeping track of 2.2 million users' activities for about 1 month during July, 2012, and collected 37 million posts finally, along with their tag profiles. In Sina Weibo, each user can specify up to 10 tags for indicating his/her interests and characteristics. The tags in Weibo are assigned with tag IDs, and each tag has an value of weight. Also each content is with certain values of tags as well. However, the weights of tags are not float values between 0 and 1 as expected, but a very larger number calculated by Sina, depending on each user's activities and characteristics, which we define as w_{it} from u_i to a tag t, and thus we will calculate the weight probability of a tag as its weight to the sum of the total weights of all tags: $w_{it} \big/ \sum_{t=1}^{N_T} w_{it}, \forall g_i, i = 1...N_T$.

B. Offline Mobility Impact

In order to model the various moving and meeting patterns of mobile users in the offline MSNs, TASA adopts the inter contact time (ICT)-based methodology from previous studies [3] [4] [7]. The mobility impact, I^M, can be defined to quantify the capability of a user to share a content object with other users by opportunistic D2D sharing, while moving in the MSN. The temporary connectivities with other users in proximity mostly relies on certain discovery mechanisms of neighbourhood, and we assume all users are synchronized by a low duty cycle for probing as proposed by eDiscovery [13]. Also we assume that the inter-contact intervals of any two mobile users follow the exponential distribution. We use λ_{ij} to denote the opportunistic contact rate of user u_i with user u_j. TASA utilizes similar epidemic modeling from [3] and we will skip calculation details due to limited space. Finally we can get the mobility impact factor I_i^M for u_i to the whole user base as: $I_i^M = \sum_{j=1}^{N} \lambda_{ij}$. Therefore based

on the evaluation of the online spreading impact and offline mobility impact of users, by given an initial pushing vector $\overrightarrow{p}$, we can finally estimate how long it may take for any user to obtain the content object via meetings, which is defined as the **Content Obtaining Delay**, t_i^*, of each user, presented as,

$$t_i^* = ObtainingDelay_i \left(\text{OnlineSpreadingImpact}_i, \text{OfflineMobilityImpact}_i \right)$$

TASA does not have to shorten the content obtaining delays for all users, but can seek the optimal pushing vector $\overrightarrow{p}$ to induce proper content obtaining delays to match with the delay sensitivity of each user, i.e., satisfactory function, which will be detailed in next subsection.

C. Content Access Delays

As studied in [9], the retweeting delays in Twitter can be mostly within the range of hundreds of seconds to thousands of seconds, or even up to several days. Therefore, users may have their own patterns of accessing contents via the SNSs, and thus may have different sensitivity requirements on their interested contents [6] [8]. We consider such a period as the **access delay**, which can be measured from online SNS datasets. From previous measurement in [3] on 2 million Sina Weibo users, nearly half of the user base may have the access delay longer than 6.5 hours. 20.38% users have delays shorter than 1 hour, and 26.79% users access SNSs with delays larger than even 1 day. Therefore, TASA will be able to send content to users who are with strong spreading and mobility impact factors but short access delays via cellular links, and then can disseminate content by D2D sharing to a certain portion of users who are with sufficient large delays for accessing the content.

In order to quantify the access delay parameters into TASA framework, we carry out modeling on user delays in terms of the probability to intend to access the content at t, which can be considered as access **satisfactory function** for each user, $Satisfactory_i()$ [3] [4]. If the content object can be obtained in user's mobile device locally immediately as soon as he/she hopes to access (with the highest probability), he/she will be mostly satisfied. We use fitting method based on Weibull distribution, which is popularly used to profile user behaviors in SNSs: $Satisfactory_i \left(t, \beta_i, k_i \right) = \frac{k_i}{\beta_i} \left(\frac{t}{\beta_i} \right)^{k_i - 1} e^{-\left(\frac{t}{\beta_i} \right)^{k_i}}, \quad t \geq 0,$ where fitting parameters β_i and k_i can identify u_i's access pattern (the PDF curve shape), and thus are considered as ***Access Delay Properties***. Therefore the satisfactory function can be presented as: $Satisfactory_i \left(ObtainingDelays, AccessDelayProperties \right)$, where the calculated obtaining delays will be the input of the satisfactory functions.

D. Optimization on Social-Aware D2D Sharing for Traffic Offloading

$$\underset{\text{InitialPushingVector:}\,\vec{p}}{\text{Maximize}:} \sum_{i=1}^{\text{All Users}} Satisfactory(\ ObtainingDelay_i(\text{OnlineSpreadingImpact}_i, \text{OfflineMobilityImpact}_i)$$

$$, \text{AccessDelayProperties}_i\ )$$

$$\text{Subject to}\ :\ \text{InitialPushingVector}\ \vec{p}\ \text{should be constrained by C},$$

where the amount of initial pushing seeds must be constrained by C. Analytically solving the above problem is hard, but we can get near-optimal results by general power series numerical methods. Also we can reversely tune and seek the needed C by given a targeted total satisfactory level. We further design a heuristic algorithm referring to [3] for finding the solution numerically, based on well-known hill-climbing algorithm. Initially we choose an easy-starting strategy, e.g., to select top C users with high I^M values, and thus we go through the user base iteratively to exchange the selecting decisions (0 or 1) of any two users if it can result in a higher value of total satisfactory. We terminate the iteration when the result converge. However, we have to skip the algorithm details in this article due to the space limit.
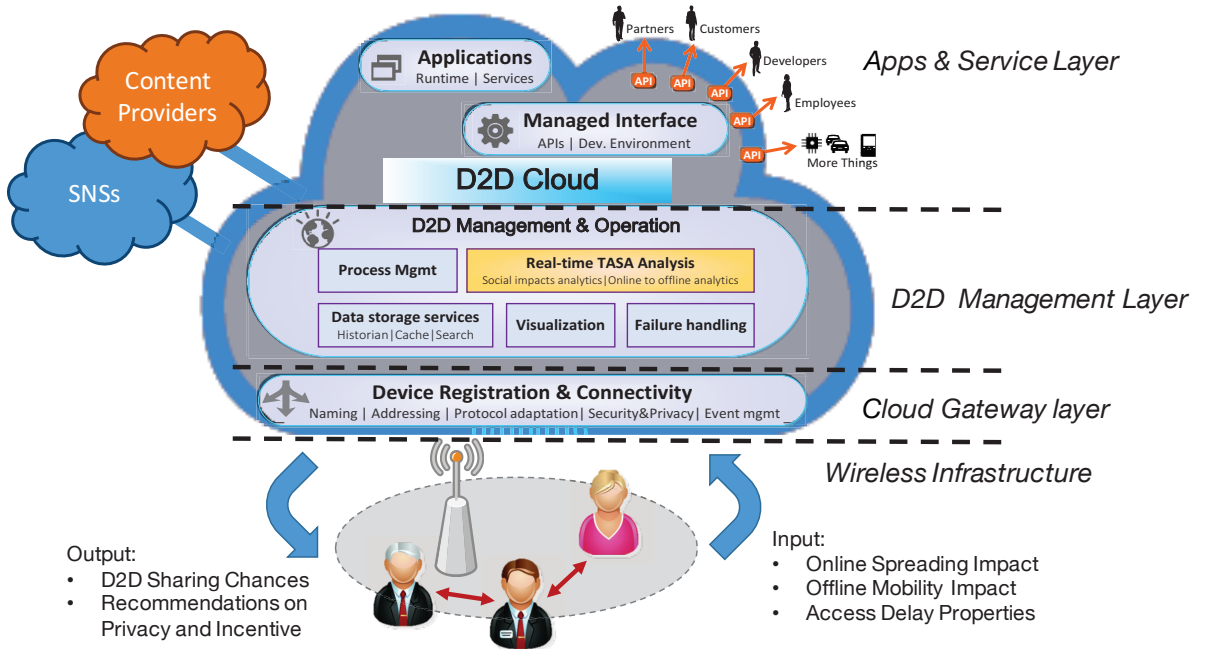
IV. TASA SYSTEM INFRASTRUCTURE

Fig. 3. "User-Infrastructure-Cloud" Interactions in TASA Architecture

A. System Architecture

Practical deployment of TASA is challenging, as it requires to collect and to process huge amount of data from online SNSs and offline MSNs, and consolidation of SNS platforms, MNOs' management of user mobility, and users' D2D transmissions. Fig. 3 shows a top-down approach to TASA social D2D sharing system architecture including three key layers: D2D management & operation platform, cloud gateway layer, and wireless infrastructure.

*1) **D2D Management and Operation Platform**:* We design the TASA based data analysis engine as a key service in basic service management layer. Consider the increasing demand of D2D-based services, contextual data with high diversity need to be collected and processed at the D2D cloud platform for further online processing and optimization. Further data mining (e.g., social similarity matching, mobility and spreading impacts) via the TASA analysis engine on the cloud platform have to be addressed before an effective content dissemination strategy can be delivered. Thus, to make the contextual data from different users be context-aware, a feasible way is to require SNSs and Content Providers (CPs) to pre-specify the definition of context for their D2D services and register them to the cloud. Further, the TASA framework needs to be jointly implemented and synchronized on both user devices and cloud platform to maintain the online and offline social data integrity. The engine of data analysis can thus understand the context of data and hence model and predict the content sharing pattern regarding individual social activities and life patterns. Note that there may be multiple roles in such a D2D cloud as shown in Fig. 3, for example, partners are cooperating entities with MNOs (e.g., other MNOs, SNSs, and CPs), customers are mobile users, developers are from 3rd-parties to improve their programs by interacting with the D2D cloud, and employees are those who manage the systems internally in MNOs, while more things is the conceptual idea that may allow social D2D to collaborate with Internet of things.

*2) **Cloud Gateway Layer**:* This layer can perform as a bridge between wireless infrastructure and D2D cloud platform, for forming a seamless online SNS to offline MSN transformation. Additionally, in order to ensure a satisfied quality of D2D service, such as maintaining an acceptable content access delay, well defined application interfaces along with efficient management protocols should be designed and agreed between both CPs and MNOs. Although current service interactions in the cloud are mostly based on Simple Object Access Protocol (SOAP) the lightweight Representation State Transfer (REST) style web service [14], is quite suitable for user mobile devices to realize D2D-based services more sharable, reusable and loose coupling. Therefore, we achieve SOAP-REST transformation by additional adapters on the cloud gateway layer.
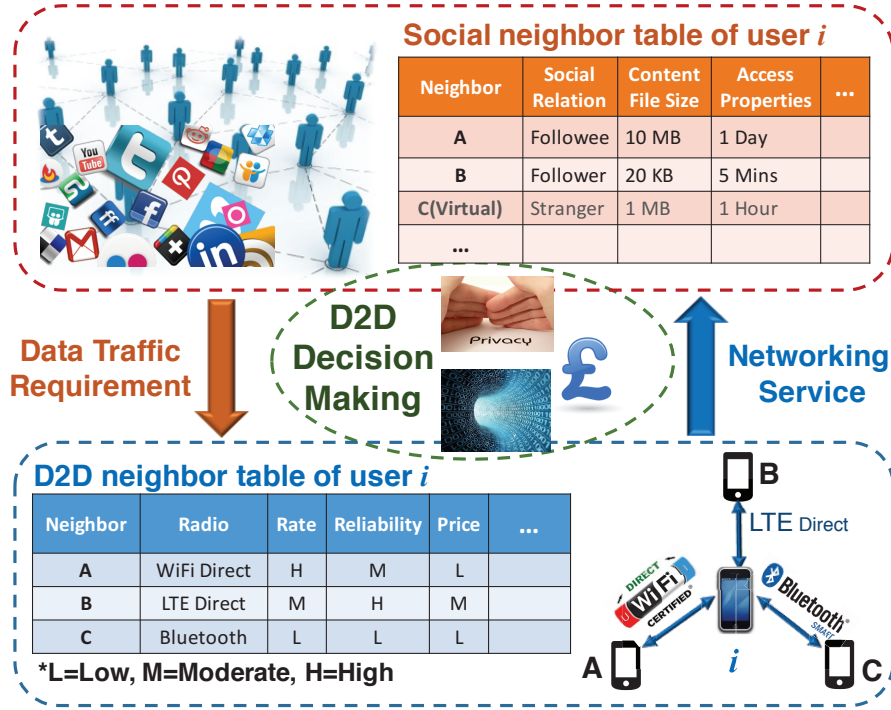
Fig. 4.   Network Protocol Support for TASA

3) Wireless Infrastructure: The interconnections between cellular networks and user devices form a hetero-geneous wireless infrastructure to offload content objects, in which the cellular networks exert a light touch by managing and controlling the allocation of secure D2D resource with alternative short-range radio interfaces. TASA will maintain the radio information of each user based on their reports and thus will manage the radio techniques for any potential connectivities. Specifically, the wireless infrastructure can provide a decentralized approach to proximity discovery and D2D communication, which is efficient, flexible, dynamic and secure, as well as privacy-enhanced, to enable proximity-based services to flourish. The wireless infrastructure needs to further consider realistic social relationships and individual user behaviors, such as selfishness and hostile, to create more effective incentive and pricing strategies and thus achieve a global optimal of content delivery in TASA's sharing-based D2D networks.

B. Components and Mechanisms for TASA

Furthermore, to support TASA in practice, new components and mechansims should be developed based on existing network infrastructure and D2D communication techniques. We highlights three key designs for TASA:

1) Social Neighbor and Temporary D2D Neighbor Tables: Both of the two tables are key data structures to respectively represent the information of online social network at the could and physical mobile D2D networks.

Examples for the two tables of a user i are illustrated in Fig. 4. Here, the social neighbor table can be straightforwardly obtained according to the users' online activities, while D2D neighbor table establishment requires to discovery opportunistically encountered devices over all possible D2D interfaces. There are many practical methods to track D2D opportunities, e.g., centralized localization by the mobility management entity (MME) in the MNO.

2) Dynamic and Distributed Networking: From networking point of view, data sharing decisions made by TASA will result in corresponding data traffic injected to the physical mobile D2D networks. To optimally balance the tradeoff between the user experience and cellular offloading efficiency, distributed and adaptive decision mechanisms should be developed to jointly optimize the traffic admission control, the selection of D2D peer devices, and the scheduling of multiple available D2D radios as shown in Fig. 4.

3) Incentivization and Privacy: As D2D transmissions cost computing resources (CPU, Memory, and I/O) and battery energy, and lead to a risk to privacy disclosure. Therefore, effective incentivization is vital to encourage the users to fulfill the D2D tasks allocated by TASA. Possible incentivization methods includes reputation-based trust management, game-theoretical auction approach, or market-centric pricing schemes for data content trading etc., which are quite interesting and challenging research direction in the future.

V. EVALUATION RESULTS

For practically testing TASA, along with the Sina Weibo dataset, we choose three mobility traces: Infocom [3], MIT [4], and SUVnet [5]. The three traces have different durations, scales, and patterns; The Infocom and MIT traces are collected by persons in campus or conference spot, who are with high contact rates, but the SUVnet trace has low contact rates, as it is collected by vehicles in a big city.

However, since there exists no any trace that may contain the activities of the same users in both SNSs and MSNs, we have to consider three possible schemes for mapping the SNS users with those MSN users regarding the three mobility traces: (1) **random**: SNS users are randomly mapped with MSN users; (2) **h-h**: both MSN and SNS users are sorted in descending order of I^S and I^M respectively, and are mapped; (3) **h-l**: both SNS and MSN users are sorted in the same way as **h-h**, but SNS users with higher I^S are mapped to MSN user with lower I^M. Since there are much more SNS users than MSN users in each trace, we pick a number of accounts from the sub-graphs of the SNS graph by using random walking method, according to the number of MSN users in each trace. This is

[3]Infocom Trace, http://crawdad.org/cambridge/haggle/20090529/

[4]MIT Trace, http://realitycommons.media.mit.edu/realitymining.html

[5]SUVnet Trace, http://wirelesslab.sjtu.edu.cn/taxi_trace_data.html

proven to be an effective way to get a representative sample of a large user base [15]. Note that the corresponding social tags and access delay patterns will be also assigned as well. We take the average values over the evaluation results across those three mapping schemes to reflect the general trends of performance.

We consider a number of varied initial pushing strategies by evaluating users' impact factors, as well as several general graph-based **viral marketing strategies**, as shown in Table I. We will investigate how much percentage of users should be selected as initial seeds for satisfying the access delay requirements from 100%, 90%, and 80% of users.

TABLE I

STRATEGIES FOR INITIAL PUSHING

p-I^M	top C users by sorting all users by I^M descendingly (similar to [4])
p-I^S	top C users by sorting all users by I^S descendingly)
p-$I^M * I^S$	top C users by sorting all users by $I^M * I^S$ descendingly (similar to [3] [7]
p-R	randomly choose C users
p-$D^{\rightarrow}$	top C users by sorting all users by outgoing node degree descendingly
p-$D^{\leftarrow}$	top C users by sorting all users by incoming node degree descendingly
p-Pr	top C users by sorting all users by PageRank score of Google descendingly
p-H	selected C users from the hill-climbing heuristic algorithm

Fig. 5 shows that, **p-H** can find best initial pushing vector (i.e., the smallest number of seeds). However, **p-R**, **p-$D^{\rightarrow}$** and **p-$D^{\leftarrow}$** perform poorly, demonstrating the ineffectiveness of simply pushing by using the graph-based strategies. In most cases, **p-$I^M * I^S$** performs good, which implies that by conjunctively considering the I^S and I^M factor by multiplication can achieve near-optimal performance in practise. **p-Pr** doesn't perform better when comparing with strategies based on impact factors. In Infocom and MIT traces, I^M-based pushing strategies can perform better than those based on I^S, which indicates the mobility factor determines more on the sharing process when nodes are with high mobility. In SUVnet traces, I^S-base ones perform better, which means the social factor controls more when nodes are with low mobility.

The required initial pushing ratio is reduced significantly if we target to satisfy 90% of all users as the worst-case users are less considered and mostly put to lower priority for satisfaction. For the MIT and the Infocom traces, only about 21.0% and 17.7% of users need to be the initial seeds on average. More interestingly, the number of initial seeds is further reduced dramatically, when satisfying 80% of users. The SUVnet trace always needs a relatively larger number of initial seeds due to their low contact rates and large user bases.
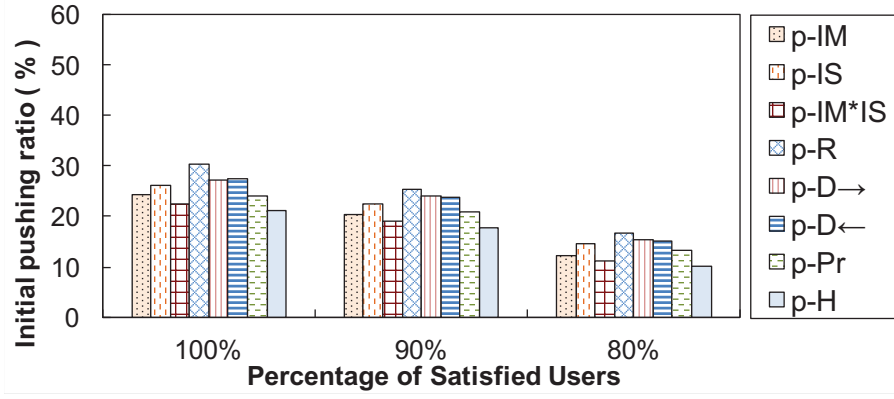
(a) Infocom
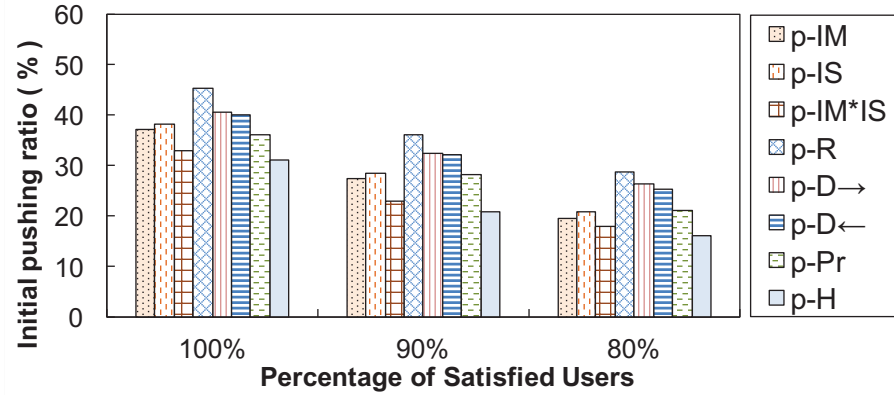
(b) MIT
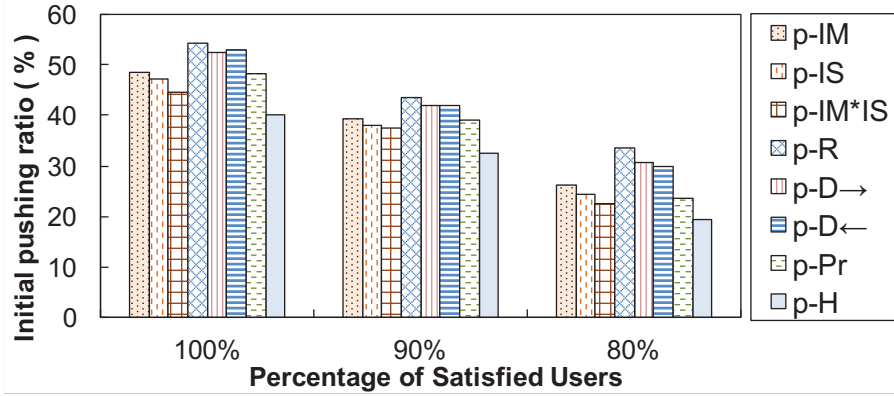
(c) SUVnet

Fig. 5. Initial Pushing Ratios to Satisfy 100%, 90%, and 80% Users

We notice that some worse-case users with both low I^S and I^M will bring ineffectiveness for opportunistic D2D sharing. It is better to push the content to them in the beginning, if they have hard access delay requirements; or it will be better to let them to carry out on-demand fetching when they get to the peaks of their access delay PDF. Generally, **p-H** performs the best but with high complexity, and **p-**$I^M * I^S$ will be a proper solution in practical with acceptable complexity and deployment efficiency.

Therefore if a user has not obtained the content (by initial pushing and thus D2D sharing) until he/she hopes to access it, TASA has to deliver it over a cellular link in the on-demand manner, resulting in less cellular data offloading. We now compare the performance of 100%, 90% and 80% of satisfied users in terms of total offloaded traffic. For example, targeting the satisfactory of 90% users, the remaining 10% users (i.e., those who have not obtained the content object) will get the content object via the cellular link by on-demand delivery when they access the content with the highest probability.

Fig. 6 shows how much traffic can be offloaded maximally on average from cellular links for the three cases, where the heuristic **p-H** strategy is used. When setting the percentage of satisfied users to 100%, 90%, and 80%, although we reduce the initial pushing ratios, the remaining 10% and 20% users still take on-demand deliveries and may instead increase the celluar traffic usage furthermore. Generally, TASA manages to offload 57.6% - 78.9% traffic to social D2D sharing.
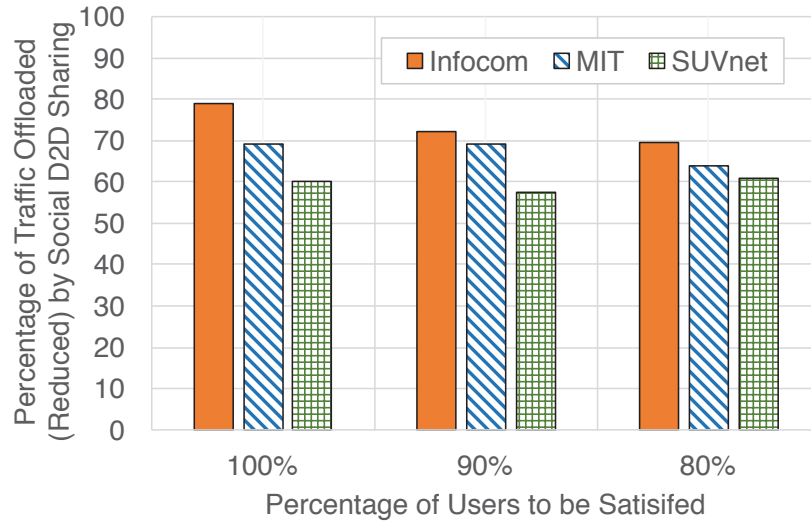

Fig. 6.   Percentage of Traffic Offloaded (Reduced) by TASA

VI. CONCLUSIONS AND DISCUSSIONS

In this article, we proposed a framework, Tag-Assisted Social-Aware opportunistic D2D sharing *TASA*, for effective mobile data offloading in mobile social networks. By analyzing users' social tags measured from online SNSs, TASA selects an optimal subset of users according to their online social spreading impacts and their offline social mobility patterns. Furthermore, the user-dependent access delays are utilized for matching the delay-tolerant content deliveries. Through extensive trace-driven simulations, we demonstrated that TASA can reduce up to 78.9% mobile traffic load while all users' access delay requirements can be satisfied.

In the near future, we will focus on large-scale practical implementations and experiments, while more investigation will be put to the security and privacy issues during social-aware sharings. Also we expect to extend TASA by exploring other promising techniques, such as cooperative integration of D2D sharing with base station caching framework, autonomous, transparent and trustworthy D2D connection management, and incorporation between D2D-based mobile crowdsensing and IoTs-enabled mobile pervasive computing techniques.

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