Implementation of Socially-Driven Learning-Based Prefetching in Mobile Online Social Networks

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Abstract:*In this paper, we discover the problem of auxiliary efficient access to social media contents on social network sitesfor mobile devices deprived of requiring mobile users to be onlineall the time.In order to offer the qualityof experience provision for mobile OSN services, in this paper,we suggest a socially-driven learning-based framework, namelySpice, for the media content prefetching to decrease the accessdelay and enhance mobile user's satisfaction. Over and done with a largescale data-driven analysis over real-life mobile Twitter tracesfrom over 17 000 users during a period of five months, we disclose that the social friendship has a great impact on user's mediacontent click behavior. To capture this effect, we conduct thesocial friendship clustering over the set of user's friends, andthen develop a cluster-based Latent Bias Model for sociallydriven learning-based prefetching prediction.*

Keywords-Social networks, mobile devices, online social network,multimedia applications, quality of experience.

I. INTRODUCTION

The phenomenal popularity of social networks, inclusive ofFacebook, Twitter, LinkedIn, Google+, and Instagram, haschanged the manner human beings interact today. Indeed, many peopledepend on these social networks to communicate with their pals,own family, and network on a day after day basis. The potential formaintain these interactions whenever everywhere seamlessly isfast turning into commonplace, and users on contemporary cellulargadgets count on to no longer simply to get admission to social networks however alsoexchange rich media contents, along with video, audio, and photos,for a better user revel in. It is stated that ninety-three% ofAndroid telephone customers in India use social networks on theirsmartphones [1] and regularly this is the cause why they purchasesmartphones inside the first location. In North America, a current IDCdataonmobile customers indicates that 70% of them get right of entry toFacebook through smartphones, and more strikingly, 40% of userssense related while the usage of Facebook, handiest trailing 43% formaking voice calls and 49% for texting [2]. In reality, the principlethe finding of the IDC document is "mobile+social=connectedness",i.e., human beings experience isolated without mobile get admission to social networks.To make sure this consistent connectedness, mobile customers subscribe (and pay for) 3G/4G information plans which might be regularly costlyand do now not paintings for a number of motives consisting of (a) wi-ficommunity availability is sporadic (accessibility of WiFi get admission tofactors, unpredictable statistics quotes in 3G networks), (b) mobiledevices are battery-powered with stringent strength budgets thatare without difficulty depleted from steady connectivity to and interactionwith WiFi/3G networks, (c) the shared network bandwidth isrestricted in public places (where users need to get entry to this data), and (d) dataplans are getting extent-pushedand therefore highly-priced.

We observe that the fundamental need (root reason) of always-on connectedness stems from the assumption that currentmobile social mobile apps, along with the mobile Facebook app,anticipate constantly-on connectivity. The modus operandi these days isthat these apps synchronize with social networks while mobile users launch the apps and mobile devices are connected tothe Internet. We trust that providing offline access for theseapps is vital for

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mobile customers so that we can interact withsocial contents when Internet get admission to is not available. There aremany scenarios wherein the offline get admission to feature is beneficial.For instance, a student takes a subway to his or her faculty. Inthe subway, the student does now not commonly have mobile Internetconnections to social community sites, and as a result the offline get admission tocharacteristic is the handiest option allowing the pupil to view andinteract with updates from his or her pals which can be prefetchedearlier than the pupil steps into the subway.The problem of optimally prefetching social media contentfrom social media companies to mobile users is greater complexthan it appears before everything look. Multiple elements contribute tothe non-uniform nature of the hassle at mobile customers, contents, and device stages. More particularly, cellular customers haveunique/personalized viewing desires and possibilities; socialmedia contents are numerous in length and importance; and networksituations can be quite dynamic due to fading, shadowing interference, and congestion on wireless/wired hyperlinks. All of theabove elements make prefetching social media contents on cellulardevices pretty tough.

Fig. 1 illustrates the considered broker/proxy architecture wheremobile users and social media providers exchange data bystaging relevant content intelligently with the supports from thebroker/proxy nodes. The goal of the broker/proxy architecture isto maximize the viewing likelihood and quality of experience ofthe prefetched social media contents while maintaining certainenergy level at mobile devices for user daily activities.

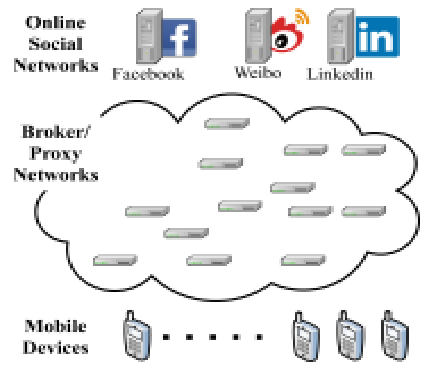

Figure 1.Considered system architecture.

We summarize the major contributions of this paper asfollows:

• We collect a large set of real-life mobile Twitter tracesfrom over 17,000 Twidere users during a period of fivemonths, and reveal the great impact of social friendshipon their media content click behavior through data-drivenanalysis.

• We conduct social friendship clustering over the set ofuser's friends, and then accordingly develop the clusterbased LBM approach for socially-driven prefetchingprediction. Trace-driven emulation shows that our proposed approach achieves an average prediction accuracyof 84.5%, which significantly outperforms the linearregression approach using tweet training features only.

• We develop a usage-adaptive prefetching schedulingscheme to account for heterogeneous users' mobile appusage pattern. In particular, we partition the horizon ofthe whole minutes of day into several period zones andtune different prefetching frequencies for different zonesadaptively.

• We comprehensively evaluate the performance of theSpice framework using trace-driven emulations on smartphones. Evaluation results show that an average Spiceuser can reduce her access delay by 80.6% at the low costof cellular data and energy consumption, which is a significant improvement over the benchmark approaches.Moreover, by enabling users to offload machine learningprocedures to a cloud server, we can achieve a speedup of a factor of 1000 over the local execution onsmartphones.

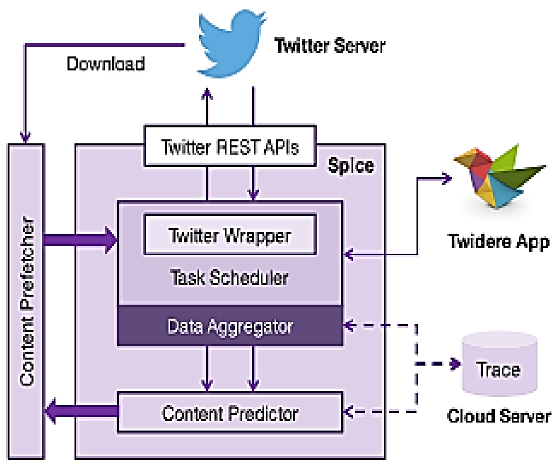

Fig. 2. Spice architecture

II. RELATED WORK

A. Spice Architecture

We now introduce the system architecture of Spice formedia content prefetching in mobile OSNs. As illustrated inFig. 2, Spice works in a user-centric manner (i.e., implementedon a user's mobile device), and collects traces about all tweetson the user's feed when accessing Twitter with the Twidereapp [9]. These traces were retrieved using the Twitter RESTAPI [10], located in the Twitter Wrapper, which is controlledby the Task Scheduler component to periodically query for new tweets on her newsfeed.Then the retrieved tweets and user information are passed tothe Data Aggregator component. To ensure the user privacy,
text content in tweets are not recorded and the anonymizationof all personal data-related fields will carried out beforedirectly storing the data on the mobile device. Later, the locallystored data is uploaded to the cloud server only for furtheranalysis when the mobile device is charging and connecting
with WiFi.The Data Aggregator also passes the received informationto the Content Predictor component, where the learningbased content prediction model is trained for predicting thelikelihood whether she would click the media in a new tweet.Specifically, this predictor would take the user's new tweets. and the relevant features of these tweets as an input to amachine learning model, in order to identify the relevantmedia content (e.g., image files) contained in these tweetsas the prefetch candidates. These media files are then to beprefetched by the Content Prefetcher component. Note that,to speed up the whole process, we offload the machine learningprocedure to a cloud server. When such a cloud server is notavailable, we can carry it out on the mobile device locally.

III. PROPOSED WORK

Logic Workflow of Spice: We then show the Logic workflow of Spice frameworkin Fig. 3 to illustrate how Spice works in more details whenfresh media contents are going to be prefetched. As what wedescribed above, Spice works in a user-centric manner and isimplemented at user side to serve as a middleware intelligentlibrary between the content context and user's prefetchingrequirements. A mobile app of OSNs, e.g., Twitter, Facebook,or WeChat etc, can interact with Spice with single third-partyAPI, judiciously rank social media files based on the resultof fully learning with one user's network utilities, app usageactiveness, and context- or social-based preference.Specifically, the Logic workflow of Spice consists of thefollowing two components, i.e., usage-adaptive schedulingand cluster-based learning. The goal here is to judiciouslydecide when should the prefetching task be invoked, andthen intelligently use a learning-based mechanism to guidewhat social media files should be prefetched. In particular,we conclude the whole prefetching mechanism as:

- **Learning.** As Spice is a socially-driven implementation for mobile media content prefetching. It is veryimportant to take care of the social friendship influence,context preference, and OSN media attributes. Towardsthis target, we develop a socially-driven learning-basedalgorithm which would be impacted by the socialfriendship and context features. We also elaborate howsignificant the learning-based mechanism to show the effectiveness and correctness of our algorithm.

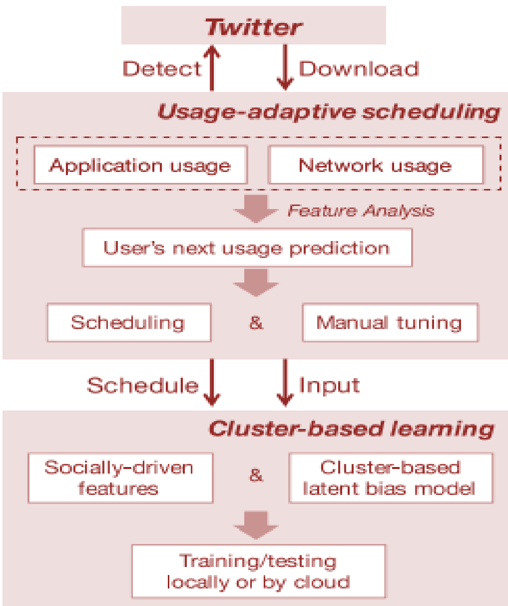

Fig. 3. Logical workflow of the Spice mobile media prefetching system.

• **Scheduling.** In Spice, we define the prefetching taskshould be not only automatic but also usage-adaptive,which leads to critical cellular data flow and batteryefficiency requirements on a preliminary that media files'loading delay can be guaranteed it is very important to decide when to prefetch accordingto user's profile, network usage preference, applicationusage activeness, and the manual tuning factors.

C. Data Collection

As mentioned above, we collect data traces from the usersusing Twidere app. This is because, although Twitter's contentsare publicly available, information about when, how, andwhere they access these social streams are not available inparticular in the mobile environment. Therefore, we collecteda large set of usage data from Twidere users1 who agreed toprovide their information to us anonymously.As the aim is to enable intelligent prefetching by identifying the tweets that the user is most interested in, a setof tweet attributes are collected as well. To this end, the Twitter Wrapper tracks the user interaction information (e.g.,retweet, favourite, or mention) of the individual tweets. Thesource of a tweet is also recorded by identifying whether thetweet is obtained from a direct friend or propagated throughfriends of others' friends. Furthermore, with the consent fromthe user, the Twidere app enables us to keep track of heractivity events when reading the tweets, e.g., watching, liking,or commenting along the timeline.

IV. CONCLUSION

Leveling at designing an intelligent mobile prefetching mechanism, in this paper we first identified the unique featuresof user's social behavior in OSN, and then suggested a novelframework of Spice based on the cluster-based LBM learningmechanism for prefetching prediction. We also developedan adaptive prefetching scheduling scheme by mining user'smobile OSN app usage pattern. We further evaluated theperformance of Spice through trace-driven emulation on smartphones.

REFERENCES

[1] C. Wu et al., "Spice: Socially-driven learning-based mobile mediaprefetching," in Proc. 35th Annu. IEEE Int. Conf. Comput. Commun.(IEEE INFOCOM), Apr. 2016, pp. 1–9.

[2] A. Lella, A. Lipsman, and K. Dreyer. U.S. Digital Futurein Focus, accessed on Apr. 2014. [Online]. Available: http://www.comscore.com/Insights/Presentations-andWhitepapers/2014/2014-US-Digital-Future-in-Focus

[3] S. Kemp. Digital, Social & Mobile Worldwide in 2015, accessed on Jan.2015. [Online]. Available: http://wearesocial.net/blog/2015/01/digitalsocial-mobile-worldwide-2015

[4] J. Holcomb, J. Gottfried, and A. Mitchell. News Use Across SocialMedia Platforms, accessed on Nov. 2013. [Online]. Available:http://www.journalism.org/2013/11/14/news-use-across-social-mediaplatforms/

[5] D. Chu, A. Kansal, J. Liu, and F. Zhao, "Mobile apps: It's time to moveup to CondOS," in Proc. 13th USENIX Conf. Hot Topics Oper. Syst.,2011, p. 16.

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Volume 04 Issue14
November 2017

[6] B. D. Higgins et al., “Informed mobile prefetching,” in Proc. 10th Int.Conf. Mobile Syst., Appl., Services, 2012, pp. 155–168.

[7] Y. Wang, X. Liu, D. Chu, and Y. Liu, “EarlyBird: Mobile prefetchingof social network feeds via content preference mining and usage patternanalysis,” in Proc. 16th ACM Int. Symp. Mobile Ad Hoc Netw.Comput.,2015, pp. 67–76.

[8] D. Rout, K. Bontcheva, D. Preo¸tiuc-Pietro, and T. Cohn, “Where’s@wally?: A classification approach to geolocating users based on theirsocial ties,” in Proc. 24th ACM Conf. Hypertext Social Media, 2013,pp. 11–20.

[9] K. Makice, Twitter API: Up and Running: Learn How to Build Applications with the Twitter API, Sebastopol, CA, USA: O’Reilly Media,2009.

[10] R. McCreadie, I. Soboroff, J. Lin, C. Macdonald, I. Ounis, andD. McCullough, “On building a reusable Twitter corpus,” in Proc. 35th

[11] M. E. J. Newman, “Modularity and community structure in networks,”Proc. Nat. Acad. Sci. USA, vol. 103, no. 23, pp. 8577–8582, 2006.

[12] P. H. Wright, “Interpreting research on gender differences in friendship:A case for moderation and a plea for caution,” J. Social Pers. Relationships, vol. 5, no. 3, pp. 367–373, 1988.

[13] A. Ahmad and L. Dey, “A k-mean clustering algorithm for mixednumeric and categorical data,” Data Knowl. Eng., vol. 63, no. 2,pp. 503–527, 2007.

[14] A. J. Nicholson and B. D. Noble, “BreadCrumbs: Forecasting mobileconnectivity,” in Proc. 14th ACM Int. Conf. Mobile Comput. Netw., 2008,pp. 46–57.

[15] L. Hong, R. Bekkerman, J. Adler, and B. D. Davison, “Learning torank social update streams,” in Proc. 35th Int. ACM SIGIR Conf. Res.Develop. Inf. Retr., 2012, pp. 651–660.

[16] L. Bottou, “Stochastic gradient descent tricks,” in Neural Networks:Tricks of the Trade. Berlin, Germany: Springer, 2012, pp. 421–436.

[17] P. Ferreira, M. McGregor, and A. Lampinen, “Caring for batteries:Maintaining infrastructures and mobile social contexts,” in Proc. 17thInt. Conf. Human-Comput. Interact. Mobile Devices Services, 2015,pp. 383–392.

[18] D. Shamma, L. Kennedy, and E. Churchill, “Tweetgeist: Can the Twittertimeline reveal the structure of broadcast events,” CSCW Horizons,pp. 589–593, 2010.

[19] L. Li, C. Chen, W. Yu, Y. Wang, and X. Guan, “Demo: An efficientand reliable wireless link for mobile video surveillance systems,” inProc. 16th ACM Int. Symp. Mobile Ad Hoc Netw.Comput. (MobiHoc),New York, NY, USA, 2015, pp. 409–410. [Online]. Available: http://doi.acm.org/10.1145/2746285.2764934

[20] L. Sang, A. Arora, and H. Zhang, “On exploiting asymmetric wirelesslinks via one-way estimation,” in Proc. 8th ACM Int. Symp. MobileAd Hoc Netw.Comput., 2007, pp. 11–21013.

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