A REVIEW ON CELLPHONE DATA ANALYSIS

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ABSTRACT

Essentially, cell phones are everywhere. Even in distant communities in underdeveloped nations, you may see someone on the street who is conversing on a cell phone. Because mobile phones are so common, they've served as a great inspiration for scientists to employ them as millions of different sensors. Mobile phones have served in only a few of its numerous applications, including distributed seismographs, as motorway traffic sensors, as medical imaging transmitters, and as communication hubs for high-level data such as reporting species invasion.

ABSTRACT: Cell phone, Data, Analysis

INTRODUCTION

To be sure, some sorts of data are restricted, and they may apply to any future uses as well. As for the contents of communications (SMS or phone talks), the operators do not record the content, therefore the material is not available to other parties. To circumvent this limitation, a distinct exemption is created for phone tapping, which is not part of this topic[1]. There are two ways in which mobile phone operators have access to all the customer information and CDRs. One is that, regardless of any privacy policies or laws regarding the protection of privacy, they provide their customers' data to other businesses. For example, if you were a mobile phone customer in the United States, your data would be provided to mobile phone companies in the United States[2-3]. When transferring a person's information, names and phone numbers should never be shared to other parties. The operators in certain countries (namely those where location data is not provided free of charge) are prohibited from using their own data for private study[4-6].

Location data and consumer data (age or gender) may also be included on CDRs. A mobile phone CDR's sheer amount of personal data makes it an exceedingly rich and interesting data source for scientists [7-10]. Recently, researchers have been using the CDR analysis to conduct their studies. As an aside, this study field had already emerged as a minor side subject in network theory by the early 2000s, and it is currently the centre of attention in the study of mobile phone datasets as a primary subject for NetMob, an international conference that has been held annually since 2009 [11-12]. A complementary issue to this conference has recently emerged, which is the examination of mobile phone datasets to support software development. Orange has launched a challenge, whose goal is to provide global access to a significant dataset from an African nation to researchers from all over the globe. Their main goal is to provide development strategies on the basis of observations gathered from the dataset for mobile phones. At the successful conclusion of the first challenge, further projects began and at the NetMob conference, the findings of the second challenge were announced [13].

RESTRICTIONS

To be sure, some sorts of data are restricted, and they may apply to any future uses as well. As for the contents of communications (SMS or phone talks), the operators do not record the content, therefore the material is not available to other parties. To circumvent this limitation, a distinct exemption is created for phone tapping, which is not part of this topic [14-16]. Additionally, mobile phone operators have access to all the customer information, such as billing records, that have been reported and CDRs, but this information does not always fall into the hands of researchers due to the laws and regulations that govern the privacy of customers in the country where the study is being conducted. When transferring a person's information, names and phone numbers should never be shared to other parties. The operators in certain countries (namely those where location data is not provided free of charge) are prohibited from using their own data for private study [17-20].

SOCIAL NETWORKS

A network made up of nodes that represent individuals making phone calls to each other is the simplest representation of a dataset of individuals making phone calls to each other. Although in the first papers about telecommunications datasets, the datasets were mostly used as examples to demonstrate the capabilities of a model or algorithm, not as a means of analysis, we cannot exclude the idea that datasets may be analysed in the future. Mobile call graphs (MCGs) differed from other complex networks, such as the web and internet, and thus required special attention [21-23].

Although the network design strategy described above looks basic, the interpretation of a link's dataset remains quite diverse. Social network research is all about understanding the relationships and patterns of contacts, yet it's possible that phone calls might have entirely different social functions. The kinds of interactions seen in CDRs are all examples of potential business calls, accidental calls, or call centres that connect to a huge number of individuals. A simple way to summarise it is that CDRs are noisy datasets. The unintentional edges must be removed during ‘cleaning' procedures. For example, in addition to reciprocity, Lambiotte et al. stipulated that the dataset required that at least one call was made in each directions and that a total of at least 1,800 minutes (about 2.5 months) were spent in the process. If it seemed as though this filtering procedure had removed a substantial number of connections from the network, in reality, only a slight weight reduction (the total number of calls each user passed in) occurred. It's likely that a threshold of three calls per month would be accepted by many, but doing a stability study around this figure may reassure that it's ok to use any figure between three and nine [24-26].

CONCLUSION

The mobile call network is best represented by an undirected network, stating that in a single phone conversation, all directions of communication are present, and the weight of the connection is determined by adding the weights of both directions. Depending on the purpose of the study, however, who initiated the call might be an essential factor in other instances. In an undirected network, the user who is making most of the calls is often the initiator, therefore how can a representative link weight be represented in this situation? There are several cases in which CDRs include information on both phone conversations and text messages, but as of now it is unclear how to combine the two bits of information. In addition, it seems that the use of text messages varies greatly over the generations, and older people use texts more often than younger people. This may inject a bias into measurement tools that only take one sort of communication into consideration [27-30].

Some other factors influencing handling of noise may include the manner to represent social relationships, which may be unidimensional, weighted, symmetric, or directional. It depends on how you answer the question. You may get drastically different replies and hence radically different network properties, which yields a wide range of plausible interpretations of the same information. Nanavati et al. prefer to use a directed network, but Onnela et al. believe an undirected network, weighted by the aggregate of inbound and outbound calls, to be a better option.

REFERNCES

1. Ahn, Y.-Y., Bagrow, J. P., & Lehmann, S. (2010). Link communities reveal multiscale complexity in networks. *Nature*, *466*(7307), 761–764. https://doi.org/10.1038/nature09182
2. Aranda-Jan, C. B., Mohutsiwa-Dibe, N., & Loukanova, S. (2014). Systematic review on what works, what does not work and why of implementation of mobile health (mHealth) projects in Africa. *BMC Public Health*, *14*(1). https://doi.org/10.1186/1471-2458-14-188
3. Caird, J. K., Johnston, K. A., Willness, C. R., Asbridge, M., & Steel, P. (2014). A meta-analysis of the effects of texting on driving. *Accident Analysis and Prevention*, *71*, 311–318. https://doi.org/10.1016/j.aap.2014.06.005
4. Case, M. A., Burwick, H. A., Volpp, K. G., & Patel, M. S. (2015). Accuracy of smartphone applications and wearable devices for tracking physical activity data. *JAMA - Journal of the American Medical Association*, *313*(6), 625–626. https://doi.org/10.1001/jama.2014.17841
5. Cerf, M., Paxon Frady, E., & Koch, C. (2009). Faces and text attract gaze independent of the task: Experimental data and computer model. *Journal of Vision*, *9*(12), 1–15. https://doi.org/10.1167/9.12.1
6. Chen, G.-H., Chen, W.-Y., Yen, Y.-C., Wang, C.-W., Chang, H.-T., & Chen, C.-F. (2014). Detection of mercury(II) ions using colorimetric gold nanoparticles on paper-based analytical devices. *Analytical Chemistry*, *86*(14), 6843–6849. https://doi.org/10.1021/ac5008688
7. Deville, P., Linard, C., Martin, S., Gilbert, M., Stevens, F. R., Gaughan, A. E., Blondel, V. D., & Tatem, A. J. (2014). Dynamic population mapping using mobile phone data. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(45), 15888–15893. https://doi.org/10.1073/pnas.1408439111
8. Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, *542*(7639), 115–

118. https://doi.org/10.1038/nature21056

9. Forbes, E. E., Hariri, A. R., Martin, S. L., Silk, J. S., Moyles, D. L., Fisher, P. M., Brown, S. M., Ryan, N. D., Birmaher, B., Axelson, D. A., & Dahl, R. E. (2009). Altered striatal activation predicting real-world positive affect in adolescent major depressive disorder. *American Journal of Psychiatry*, *166*(1), 64–73. https://doi.org/10.1176/appi.ajp.2008.07081336
10. Hoque, R., & Sorwar, G. (2017). Understanding factors influencing the adoption of mHealth by the elderly: An extension of the UTAUT model. *International Journal of Medical Informatics*, *101*, 75–84. https://doi.org/10.1016/j.ijmedinf.2017.02.002
11. Isaacman, S., Becker, R., Cáceres, R., Kobourov, S., Martonosi, M., Rowland, J., & Varshavsky, A. (2011). Identifying important places in people's lives from cellular network data. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *6696 LNCS*, 133–151. https://doi.org/10.1007/978-3-642-21726-5_9
12. Jenaro, C., Flores, N., Gómez-Vela, M., González-Gil, F., & Caballo, C. (2007). Problematic internet and cell-phone use: Psychological, behavioral, and health correlates. *Addiction Research and Theory*, *15*(3), 309–320. https://doi.org/10.1080/16066350701350247
13. Junco, R., & Cotten, S. R. (2012). No A 4 U: The relationship between multitasking and academic performance. *Computers and Education*, *59*(2), 505–514. https://doi.org/10.1016/j.compedu.2011.12.023
14. Klausen, J. (2015). Tweeting the Jihad: Social media networks of Western foreign fighters in Syria and Iraq. *Studies in Conflict and Terrorism*, *38*(1), 1–22. https://doi.org/10.1080/1057610X.2014.974948
15. Lester, R. T., Ritvo, P., Mills, E. J., Kariri, A., Karanja, S., Chung, M. H., Jack, W., Habyarimana, J., Sadatsafavi, M., Najafzadeh, M., Marra, C. A., Estambale, B., Ngugi, E., Ball, T. B., Thabane, L., Gelmon, L. J., Kimani, J., Ackers, M., & Plummer, F. A. (2010). Effects of a mobile phone short message service on antiretroviral treatment adherence in Kenya (WelTel Kenya1): A randomised trial. *The Lancet*, *376*(9755), 1838–1845. https://doi.org/10.1016/S0140-6736(10)61997-6
16. Liang, Y., Reyes, M. L., & Lee, J. D. (2007). Real-time detection of driver cognitive distraction using support vector machines. *IEEE Transactions on Intelligent Transportation Systems*, *8*(2), 340–350. https://doi.org/10.1109/TITS.2007.895298
17. Lowres, N., Neubeck, L., Salkeld, G., Krass, I., McLachlan, A. J., Redfern, J., Bennett, A. A., Briffa, T., Bauman, A., Martinez, C., Wallenhorst, C., Lau, J. K., Brieger, D. B., Sy, R. W., & Ben Freedman, S. (2014). Feasibility and cost-effectiveness of stroke prevention through community screening for atrial fibrillation using iPhone ECG in pharmacies: The SEARCH-AF study. *Thrombosis and Haemostasis*, *111*(6), 1167–1176. https://doi.org/10.1160/TH14-03-0231
18. Mateo, G. F., Granado-Font, E., Ferré-Grau, C., & Montaña-Carreras, X. (2015). Mobile phone apps to promote weight loss and increase physical activity: A systematic review and meta-analysis. *Journal of Medical Internet Research*, *17*(11). https://doi.org/10.2196/jmir.4836
19. Morone, F., & Makse, H. A. (2015). Influence maximization in complex networks through optimal percolation. *Nature*, *524*(7563), 65–68. https://doi.org/10.1038/nature14604
20. Morris, M. E., Kathawala, Q., Leen, T. K., Gorenstein, E. E., Guilak, F., Labhard, M., & Deleeuw, W. (2010). Mobile therapy: Case study evaluations of a cell phone application for emotional self-awareness.

Journal of Medical Internet Research, *12*(2). https://doi.org/10.2196/jmir.1371

21. Pei, T., Sobolevsky, S., Ratti, C., Shaw, S.-L., Li, T., & Zhou, C. (2014). A new insight into land use classification based on aggregated mobile phone data. *International Journal of Geographical Information Science*, *28*(9), 1988–2007. https://doi.org/10.1080/13658816.2014.913794
22. Pierannunzi, C., Hu, S. S., & Balluz, L. (2013). A systematic review of publications assessing reliability and validity of the Behavioral Risk Factor Surveillance System (BRFSS), 2004-2011. *BMC Medical Research Methodology*, *13*(1). https://doi.org/10.1186/1471-2288-13-49
23. Poggio, T., & Bizzi, E. (2004). Generalization in vision and motor control. *Nature*, *431*(7010), 768–774. https://doi.org/10.1038/nature03014
24. Potlapally, N. R., Ravi, S., Raghunathan, A., & Jha, N. K. (2006). A study of the energy consumption characteristics of cryptographic algorithms and security protocols. *IEEE Transactions on Mobile Computing*, *5*(2), 128–143. https://doi.org/10.1109/TMC.2006.16
25. Ratti, C., Frenchman, D., Pulselli, R. M., & Williams, S. (2006). Mobile landscapes: Using location data from cell phones for urban analysis. *Environment and Planning B: Planning and Design*, *33*(5), 727–748. https://doi.org/10.1068/b32047
26. Saeb, S., Zhang, M., Karr, C. J., Schueller, S. M., Corden, M. E., Kording, K. P., & Mohr, D. C. (2015). Mobile phone sensor correlates of depressive symptom severity in daily-life behavior: An exploratory study. *Journal of Medical Internet Research*, *17*(7). https://doi.org/10.2196/jmir.4273
27. Alyas, T., Tabassum, N., Naseem, S., Ahmed, F. and Ein, Q. T. (2014) “Learning-Based Routing in Cognitive Networks”, IARS’ International Research Journal. Vic. Australia, 4(2). doi: 10.51611/iars.irj.v4i2.2014.40.
28. Silva, B. M. C., Rodrigues, J. J. P. C., de la Torre Díez, I., López-Coronado, M., & Saleem, K. (2015). Mobile-health: A review of current state in 2015. *Journal of Biomedical Informatics*, *56*, 265–272. https://doi.org/10.1016/j.jbi.2015.06.003
29. Strayer, D. L., & Drews, F. A. (2007). Cell-phone-induced driver distraction. *Current Directions in Psychological Science*, *16*(3), 128–131. https://doi.org/10.1111/j.1467-8721.2007.00489.x
30. Varnfield, M., Karunanithi, M., Lee, C.-K., Honeyman, E., Arnold, D., Ding, H., Smith, C., & Walters, D. L. (2014). Smartphone-based home care model improved use of cardiac rehabilitation in postmyocardial infarction patients: Results from a randomised controlled trial. *Heart*, *100*(22), 1770–1779. https://doi.org/10.1136/heartjnl-2014-305783
31. Zangheri, M., Cevenini, L., Anfossi, L., Baggiani, C., Simoni, P., Di Nardo, F., & Roda, A. (2015). A simple and compact smartphone accessory for quantitative chemiluminescence-based lateral flow immunoassay for salivary cortisol detection. *Biosensors and Bioelectronics*, *64*, 63–68. https://doi.org/10.1016/j.bios.2014.08.048