Towards Estimating Happiness using Social Sensing: Perspectives on Organizational Social Network Analysis

Martin Atzmueller[1,2], Daan Kolkman[2], Werner Liebregts[2,3], and Arjan Haring[2]

[1] Tilburg University, Department of Cognitive Science and Artificial Intelligence (CSAI), Warandelaan 2, 5037 AB Tilburg, The Netherlands

[2] Jheronimus Academy of Data Science (JADS), Sint Janssingel 92, 5211 DA 's-Hertogenbosch, The Netherlands

[3] Tilburg University, Tilburg Institute of Governance (TIG), Tilburg School of Economics and Management (TiSEM), The Netherlands

{m.atzmuller,d.a.kolkman,w.j.liebregts}@uvt.nl, a.haring@jads.nl

Abstract. Social sensing provides many opportunities for observing human behavior utilizing objective (sensor) measurements. This paper describes an approach for analyzing organizational social networks capturing face-to-face contacts between individuals. Furthermore, we outline perspectives and scenarios for an extended analysis in order to estimate happiness in the context of organizational social networks.

Keywords: social sensing; social network analysis; happiness; organizational networks

1 Introduction

With the emergence of the Internet of Things (IoT), smart devices, and ubiquitous computing, social sensing enables the collection of multi-modal interaction data at an unprecedented scale. Social sensing methods have been applied in diverse domains, e. g., [1, 9, 12, 24, 30, 39, 41, 42, 51]). Their insights enable the understanding of human behavior, as well as to enable structural modeling and the analysis of social interaction structures. Specifically, social networks in the context of organizations capture individual behavior as well as group-behavioral patterns. Then, these can be used for potentially estimating both individual and collective happiness, also relating to well-being.

This paper discusses perspectives on the analysis of complex organizational networks as well as estimating happiness using social sensing. Furthermore, we describe a computational social sensing method using wearable sensors combined with first results on analyzing organizational social networks. After that, we provide an outlook on how to estimate happiness in two organizational social network settings, i. e., in student groups as well as in groups involved in startups.

The remainder of the paper is structured as follows: Section 2 discusses related work. After that, Section 3 presents a conceptual overview on the concept of happiness and its possible estimation. Section 4 outlines the social sensing method and discusses first results. Section 5 discusses according social network analysis methods and a social sensing framework for estimating happiness. Finally, Section 6 concludes with a summary and outlines opportunities for future work.

2 Related Work

This section first discusses related work on social network analysis and social sensing, before we focus on conceptual approaches for estimating happiness in the next section.

2.1 Analysis of Social Interaction Networks and Group Behavior

The analysis of interaction and groups, and their evolution, respectively, are prominent topics in the social sciences, e. g., [20, 34, 55, 57]. Wasserman and Faust [59] discuss social network analysis in depth, and provide an overview on the analysis of cohesive subgroups in graphs. Arrow et al. [4] specifically focus on the behavior of small groups. First analyses concerning group contact evolution have been reported in [13], where the temporal evolution of smaller groups (up to size four) were analyzed. Brodka et al. [18] investigate group formation and group evolution discovery in social networks.

This paper considers social interaction networks of face-to-face contacts captured using social sensing as outlined below. We focus on analyzing dynamic contact and group behavior in a social network analysis and mining setting, e. g., [6]. Furthermore, we focus on indicators regarding "social event happiness" given the contact dynamics.

2.2 Social Sensing

The analysis of human contact patterns and their underlying structure is an interesting and challenging task. An analysis, e. g., using proximity information collected by bluetooth devices as a proxy for human proximity is presented in [23]. However, given the range of interaction of bluetooth devices, the detected proximity does not necessarily correspond to face-to-face contacts [14].

The SocioPatterns collaboration developed an infrastructure that detects close-range and face-to-face proximity (1-1.5 meters) of individuals wearing proximity tags with a temporal resolution of 20 seconds [19].[4] This infrastructure has been deployed in various environments for studying the dynamics of human contacts, e. g., at conferences [19, 40]. They presented an application that combines online and offline data from conference attendees [2], similar to the Conferator [10] system. The SocioPatterns (hardware) framework provides also the technical basis of the Ubicon software platform [8][5] for observing social and physical activities, such as (social) interactions but also relating to spatio-temporal processes [53]. In this context, Atzmueller et al. [11] analyze the interactions and dynamics of the behavior of participants at conferences; similarly, the connection between research interests, roles and academic jobs of conference attendees is further analyzed in [40]. Another approach for observing human face-to-face proximity and communication is the Sociometric Badge [60].[6] It records more details of the social interaction, but requires significantly larger devices.

In this paper, we outline an exemplary study with first results, where we utilize the Sociopattern proximity tags and the Ubicon platform [8] for observing physical (face-to-face) interactions, towards objectively estimating happiness indicators.

[4] http://www.sociopatterns.org
[5] http://www.ubicon.eu
[6] http://hd.media.mit.edu/badges

3 Happiness – An Conceptual Overview

In recent years, we have seen a sharp increase in publications on the "science of happiness", and a concomitant rise in the public interest for such studies. The underlying rationale of such works suggests that the scientific method can be applied to measure, study, and better understand happiness. Since our methods have improved, some believe conventional ways of measuring well-being and happiness are no longer elusive [15]. This renewed academic as well as popular interest has had a considerable impact; increasingly, well-being and happiness are framed as a skill that can be learned. Not surprisingly, an industry consisting of motivational speakers, self-help books, and other personal development professionals now aim to assist in our pursuit of happiness [31].

Traditionally, happiness is conceptualized as the subjective part of the concept of well-being. Bartram explains that a distinction can be made between objective well-being and subjective well-being [15]. The first can be readily conceptualized and measured; it includes, amongst other things, income and access to goods. The latter, however, is entwined with experiences and emotions and therefore often harder to determine. That is, emotions are harder to observe in other people, as most people would only be able to state whether they themselves are happy or not. Subjective well-being can be divided into two components: (1) Happiness, the affective component, and (2) life satisfaction, a cognitive component that covers our self-evaluations about how well we feel our lives are going. While – or perhaps because – the concept of happiness is relatable for anyone, there is no shortage of definitions in the literature. Examples include "feeling good" [36], "a positive emotional state" [28] and a "whimsical state of mind" [58]. The common process of developing a sound measure of happiness requires researchers to make arbitrary judgments about what questions to include, to whom to ask them, and what phrasing to use. Moreover, subsequently adjusting the measurements through statistical analysis requires further normative judgment from the researcher [3].

Most (conventional) research on happiness employs surveys that ask participants to score their happiness on Likert scales. Other forms of data on happiness include "experience sampling", which is a diary method that asks participants to score and record their happiness several times a day [15]. A related body of research has considered a wealth of determinants and correlates of happiness. One of the most researched areas includes correlations between income and happiness, an area influenced by studies in behavioral economic [31], e. g., that those with higher incomes are happier than those with lower incomes, but an increase in one's income generally does not lead to an increase in happiness [25]. Rather, some would suggest that society's increase in wealth has gone hand in hand with greater levels of distress [5]. However, there are good reasons to question the applicability of the current scientific method to the study of happiness. First, scientists are not the only authority on norms. Given that we are all familiar with making judgments on "what makes us happy", it seems problematic to grant academia a privileged position to determine what is – or is not – covered by the concept [3]. Second, we can consider how happiness is typically measured. Most of the previous contributions use surveys, or rely on self-report diaries to score happiness. Both methods require considerable effort from participants and can suffer from decreasing completion rates and hindsight bias. This paper contributes to the second challenge aiming at the development of a new approach for estimating happiness using wearable sensors.

4 Method

This section discusses perspectives on estimating happiness using social sensing. For that, we sketch a method for social sensing using wearable sensors that capture face-to-face interactions between participants. In particular, this is targeted at observing interactions in social groups. We exemplify the method using an analysis in the context of the career perspective day 2017 at the Jheronimus Academy of Data Science. Here, we discuss preliminary results as well as first directions towards the formalization of happiness indicators regarding (social) groups, e. g., in educational settings.

4.1 Observing Interactions in Social Groups using Wearable Sensors

The estimation of happiness in educational groups, e. g., student groups is relevant, since there is a link between academic achievement and happiness, e. g., [16, 29, 50]. As a first preliminary experiment for estimating happiness, we applied wearable sensors at a career perspective data, observing face-to-face contacts between participants (students) and companies. The context of the experiment was given by the JADS Career Perspective Day. It aimed at attracting student participants who were considering a career in the world of data science, i. e., in order to inform about expectations about working as data scientist, how businesses are applying data science, to get insights into personal career opportunities, and – in particular – to meet companies. At the JADS Career Perspective Day on May 19th, 2017, we offered wearable sensors (Sociopatterns proximity tags) to the students. In addition, we tagged stands of companies in order to estimate the contacts between participants and companies. In that way, we could extract a bi-modal network of participant-company interactions. We sketch first findings below.

Similar to the scenario of student groups, happiness can also be estimated in the context of startups (i. e., entrepreneurial happiness). This is relevant because there is evidence of a link between productivity and happiness, cf., [46–48]. Also, we believe that there might be a link between happiness and other relevant factors, like creativity and focus, which we also aim to examine in further experiments.

4.2 First Results

As outlined above, proximity tags were offered to participants. In total, 118 participants volunteered to take part in the experiment.[7] Furthermore, 35 tags were used for tagging company stands. Figure 1 shows the respective degree distributions of participants and company stands, respectively. These indicate the "contact distributions" with respect to unique contacts to participants and company stands, respectively. Overall, we can see that the participant degree distribution is left-shifted (towards a heavy-tailed distribution), while the stand degree distribution has a more gaussian-like distribution. From both, we could model indicators about "event happiness" regarding the expectations of companies and participants, based on statistical measures like the corresponding nodes' degree compared to the mean degree of the nodes in the network, similar to distributional analyses as a proxy for social phenomena [44, 45]. These can be validated using surveys, by comparison to the overall distribution, or using appropriate null-models.

[7] Study participants also gave their informed consent for the use of their data in scientific studies.

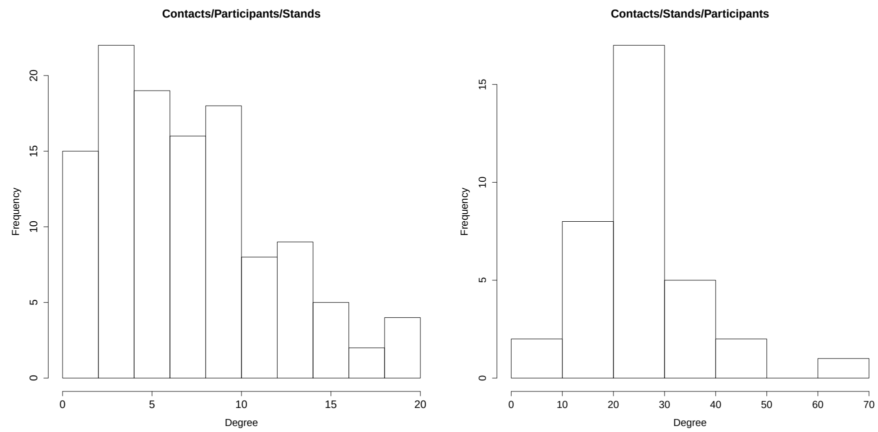

Fig. 1. Degree distributions of two complementary contact perspectives at the JADS Career Perspective Day: Left – participants to stands, Right – stands to participants

5 Discussion

This section first discusses social network analysis and its implications towards estimating happiness. After that, we sketch a framework towards measuring happiness using wearable sensors and social network analysis methods.

5.1 Organizational Social Network Analysis and Its Implications

Mitchell [43] once defined a social network as "a specific set of linkages among a defined set of persons, with the additional property that the characteristics of these linkages as a whole may be used to interpret the social behavior of the persons involved" (p. 2). Social network analysis [59] is concerned with both the structure and the characteristics of relationships between all objects that are part of a certain system. Moreover, such analyses seek to identify the determinants and consequences of all present relationships. Since organizations can be viewed as social groupings, Tichy et al. [56] propose to use a social network approach in organizational settings, which is rooted in the fields of anthropology (e. g., [17, 38]), role theory (e. g., [33]), and sociology (e. g., [54]). Ever since, organizational social network analysis has been applied in a variety of ways in at least as many different contexts. For social network analysis, including those in organizational settings, objective, subjective as well as sociometric data can be collected. Hitherto, for the most part, network data have been collected by means of attributional/reputational, decisional, interactional, and positional analyses, each with their own strengths and weaknesses [56]. For example, interactional analysis leads to reliable data, but is a rather costly method in terms of administration and management. Kilduff & Brass [35] highlight current leading ideas in organizational social network research, such as the focus on (dyadic) relationships between actors, and that such social relations are generally believed to impact various outcomes at the individual and group level. Using a longitudinal research design, for example, Fowler &

Christakis [27] demonstrate a link between both direct and indirect ties on happiness. That is, an individual's happiness appears to be associated with the happiness of individuals up to three degrees removed from the actors under investigation. However, Fowler & Christakis [27] did not investigate organizational social networks in particular. A meta-analysis by Pinquart & Sörensen [49] combines findings from hundreds of past empirical studies, and arrives at the conclusion that, amongst others, having social contacts is positively associated with subjective well-being. Especially the quality of contacts seems to matter. Neither the study by Fowler & Christakis [27] nor the one by Pinquart & Sörensen [49] based the analysis on objective measures of happiness or well-being.

5.2 Data-Driven Framework for Estimating Happiness

Current research on happiness mainly focuses on self-reporting like the day reconstruction method [32] and experience sampling [21]. Although these research methods have strong advantages, they also have disadvantages which can be compensated by use of mobile devices, sensor networks and wearable sensors.

Figure 2 depicts a sketch of the data-driven framework for estimating happiness using social sensing: In that way, objective data can be measured in order to allow predictions, and ultimately also to influence individuals (for adapting/change their behavior) in order to increase their well-being and happiness, e. g., using recommendations. In particular, self reporting is in essence intrusive. It requires effort from participants

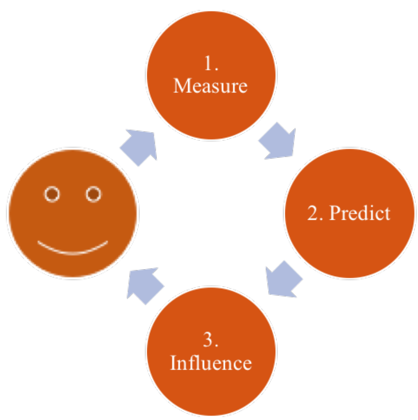

Fig. 2. Proposed data-driven framework for estimating happiness using social sensing.

which negatively affects participation rate. And by being intrusive self-reporting never really captures the happiness of participants in the moment of reporting, the reporting actually takes participants out of the moment, so to say. In the case of the day reconstruction method we rely on the participants ability to recollect and remember happiness measurements at the end of a day, which makes these reports susceptible to hindsight bias and desirability bias. By establishing non-verbal measurements of happiness we aim to increase participation rates and hope to find a closer proxy for experienced happiness in the moment.

6 Conclusions

In this paper, we focused on perspectives for estimating happiness using social sensing in the context of complex organizational networks. In particular, we described a computational social sensing method using wearable sensors for observing physical interaction networks. For that, we discussed first results, also towards deriving according happiness indicators given by the respective contact behavior. Finally, we provided an outlook on how to estimate happiness, and discussed a data-driven framework that incorporates estimation, prediction, as well as recommendations in order to influence participants for increasing their experienced level of happiness and well-being.

In the context of this paper, it is important to note that we so far focus on the first component of happiness (as discussed above), i. e., happiness as the affective component in event-based or group-based scenarios like student groups, startups, or conferences etc. For future work, we then aim for different instantiations of the framework sketched above. Once we have collected the non-verbal data of participants by means of social interaction data we can then develop predictive models based on this data, using social network analysis and mining methods, e. g., [6, 7, 12, 22, 26, 37, 52]. We will then use the individual predictions to recommend activities to participants via the same wearable device that captures the social interaction data. Following these recommendations we expect participants to increase their experienced happiness in the moment.

References

1. Aggarwal, C.C., Abdelzaher, T.: Social Sensing. In: Managing and Mining Sensor Data, pp. 237–297. Springer, Heidelberg, Germany (2013)
2. Alani, H., Szomszor, M., Cattuto, C., den Broeck, W.V., Correndo, G., Barrat, A.: Live Social Semantics. In: Intl. Semantic Web Conference (ISWC). pp. 698–714 (2009)
3. Alexandrova, A.: A Philosophy for the Science of Well-being. Oxford Univ. Press (2017)
4. Arrow, H., McGrath, J.E., Berdahl, J.L.: Small Groups as Complex Systems: Formation, Coordination, Development, and Adaptation. Sage Publications (2000)
5. Atherton, John; Graham, Elaine;Steedman, I.: The Practices of Happiness (2011)
6. Atzmueller, M.: Data Mining on Social Interaction Networks. JDMDH 1 (June 2014)
7. Atzmueller, M.: Detecting Community Patterns Capturing Exceptional Link Trails. In: Proc. IEEE/ACM ASONAM. IEEE Press, Boston, MA, USA (2016)
8. Atzmueller, M., Becker, M., Kibanov, M., Scholz, C., Doerfel, S., Hotho, A., Macek, B.E., Mitzlaff, F., Mueller, J., Stumme, G.: Ubicon and its Applications for Ubiquitous Social Computing. New Review of Hypermedia and Multimedia 20(1), 53–77 (2014)
9. Atzmueller, M., Becker, M., Mueller, J.: Collective Sensing Platforms. In: Participatory Sensing, Opinions and Collective Awareness, pp. 115–133. Springer (2017)
10. Atzmueller, M., Benz, D., Doerfel, S., Hotho, A., Jäschke, R., Macek, B.E., Mitzlaff, F., Scholz, C., Stumme, G.: Enhancing Social Interactions at Conferences. it 53(3) (2011)
11. Atzmueller, M., Doerfel, S., Hotho, A., Mitzlaff, F., Stumme, G.: Face-to-Face Contacts at a Conference: Dynamics of Communities and Roles. In: Modeling and Mining Ubiquitous Social Media, LNAI, vol. 7472. Springer, Heidelberg, Germany (2012)
12. Atzmueller, M., Hilgenberg, K.: Towards Capturing Social Interactions with SDCF: An Extensible Framework for Mobile Sensing and Ubiquitous Data Collection. In: Proc. MSM 2013, Hypertext. ACM Press, New York, NY, USA (2013)

13. Barrat, A., Cattuto, C.: Temporal Networks, chap. Temporal Networks of Face-to-Face Human Interactions. Understanding Complex Systems, Springer (2013)
14. Barrat, A., Cattuto, C., Colizza, V., Pinton, J.F., den Broeck, W.V., Vespignani, A.: High Resolution Dynamical Mapping of Social Interactions with Active RFID. PLoS ONE 5(7) (2008)
15. Bartram, D.: Elements of a Sociological Contribution to Happiness Studies. Sociology Compass 6(8), 644–656 (2012)
16. Baumeister, R.F., Campbell, J.D., Krueger, J.I., Vohs, K.D.: Does High Self-Esteem Cause Better Performance, Interpersonal Success, Happiness, or Healthier Lifestyles? Psychological science in the public interest 4(1), 1–44 (2003)
17. Blau, P.M.: Exchange and Power in Social Life. Transaction Publishers (1964)
18. Bródka, P., Saganowski, S., Kazienko, P.: GED: The Method for Group Evolution Discovery in Social Networks. SNAM 3(1), 1–14 (2011)
19. Cattuto, C., Van den Broeck, W., Barrat, A., Colizza, V., Pinton, J.F., Vespignani, A.: Dynamics of Person-to-Person Interactions from Distributed RFID Sensor Networks. PLoS ONE 5(7) (2010)
20. Coleman, J.: Foundations of Social Theory. Belknap Press of Harvard Univ. Press, Cambridge, Mass. (2000)
21. Csikszentmihalyi, M.: Toward a Psychology of Optimal Experience. In: Flow and the foundations of positive psychology, pp. 209–226. Springer (2014)
22. Duivesteijn, W., Feelders, A.J., Knobbe, A.: Exceptional Model Mining. Data Mining and Knowledge Discovery 30(1), 47–98 (2016)
23. Eagle, N., Pentland, A., Lazer, D.: From the Cover: Inferring Friendship Network Structure by using Mobile Phone Data. PNAS 106, 15274–15278 (2009)
24. Eagle, N., Pentland, A.S.: Reality Mining: Sensing Complex Social Systems. Personal and Ubiquitous Computing 10(4), 255–268 (2006)
25. Easterlin, R.A.: Does Money Buy Happiness? The public interest (30), 3 (1973)
26. Falih, I., Grozavu, N., Kanawati, R., Bennani, Y.: A Recommendation System Based on Unsupervised Topological Learning. In: Proc. ICONIP. pp. 224–232. Springer (2015)
27. Fowler, J.H., Christakis, N.A.: Dynamic Spread of Happiness in a Large Social Network: Longitudinal Analysis over 20 Years in the Framingham Heart Study. Bmj 337, a2338 (2008)
28. Haybron, D.M.: Happiness, the Self and Human Flourishing. Utilitas 20(01), 21–49 (2008)
29. Huebner, E.S., Gilman, R.: Toward a Focus on Positive Psychology in School Psychology. School Psychology Quarterly 18(2) (2003)
30. Isella, L., Romano, M., Barrat, A., Cattuto, C., Colizza, V., Van den Broeck, W., Gesualdo, F., Pandolfi, E., Ravà, L., Rizzo, C., Tozzi, A.E.: Close Encounters in a Pediatric Ward: Measuring Face-to-Face Proximity and Mixing Patterns with Wearable Sensors. PLOS ONE 6(2), e17144 (02 2011)
31. Jugureanu, A.: A Short Introduction to Happiness in Social Sciences. Belvedere Meridionale 28(1), 55–71 (2016)
32. Kahneman, D., Krueger, A.B., Schkade, D.A., Schwarz, N., Stone, A.A.: A Survey Method for Characterizing Daily Life Experience: The Day Reconstruction Method. Science 306(5702), 1776–1780 (2004)
33. Katz, D., Kahn, R.L.: The Psychology of Organizations. New York: HR Folks International (1966)
34. Kibanov, M., Atzmueller, M., Scholz, C., Stumme, G.: Temporal Evolution of Contacts and Communities in Networks of Face-to-Face Human Interactions. Science China 57 (2014)
35. Kilduff, M., Brass, D.J.: Organizational Social Network Research: Core Ideas and Key Debates. Academy of management annals 4(1), 317–357 (2010)
36. Layard, R.: Happiness: Lessons From a New Science. Penguin UK (2011)

37. Lemmerich, F., Becker, M., Atzmueller, M.: Generic Pattern Trees for Exhaustive Exceptional Model Mining. In: Proc. ECML/PKDD. Springer, Heidelberg, Germany (2012)
38. Lévi-Strauss, C.: The Elementary Structures of Kinship. No. 340, Beacon Press (1971)
39. Liu, Y., Liu, X., Gao, S., Gong, L., Kang, C., Zhi, Y., Chi, G., Shi, L.: Social Sensing: A New Approach to Understanding Our Socioeconomic Environments. Annals of the Association of American Geographers 105(3), 512–530 (2015)
40. Macek, B.E., Scholz, C., Atzmueller, M., Stumme, G.: Anatomy of a Conference. In: Proc. ACM Hypertext. pp. 245–254. ACM, New York, NY, USA (2012)
41. Madan, A., Cebrian, M., Lazer, D., Pentland, A.: Social Sensing for Epidemiological Behavior Change. In: Proc. ACM UbiComp. pp. 291–300. ACM (2010)
42. Madan, A., Moturu, S.T., Lazer, D., Pentland, A.S.: Social Sensing: Obesity, Unhealthy Eating and Exercise in Face-to-Face networks. In: Wireless Health. pp. 104–110. ACM (2010)
43. Mitchell, J.C.: The Concept and Use of Social Networks. Social Networks in Urban Situations (1969)
44. Mitzlaff, F., Atzmueller, M., Hotho, A., Stumme, G.: The Social Distributional Hypothesis. Journal of Social Network Analysis and Mining 4(216), 1–14 (2014)
45. Mitzlaff, F., Atzmueller, M., Stumme, G., Hotho, A.: Semantics of User Interaction in Social Media. In: Ghoshal, G., Poncela-Casasnovas, J., Tolksdorf, R. (eds.) Complex Networks IV, Studies in Computational Intelligence, vol. 476 (2013)
46. Naudé, W., Amorós, J.E., Cristi, O.: "Surfeiting, The Appetite May Sicken": Entrepreneurship and the Happiness of Nations (2012)
47. Oswald, A.J.: Happiness and Economic Performance. Economic Journal 107(445) (1997)
48. Oswald, A.J., Proto, E., Sgroi, D.: Happiness and Productivity. Journal of Labor Economics 33(4), 789–822 (2015)
49. Pinquart, M., Sörensen, S.: Influences of Socioeconomic Status, Social Network, and Competence on Subjective Well-Being in Later Life: A Meta-Analysis. Psychology and Aging 15(2), 187 (2000)
50. Quinn, P.D., Duckworth, A.L.: Happiness and Academic Achievement: Evidence for Reciprocal Causality. In: Annual Meeting of the American Psychological Society. vol. 24 (2007)
51. Salathé, M., Bengtsson, L., Bodnar, T.J., Brewer, D.D., Brownstein, J.S., Buckee, C., Campbell, E.M., Cattuto, C., Khandelwal, S., Mabry, P.L., Vespignani, A.: Digital Epidemiology. PLOS Computational Biology 8(7), e1002616 (07 2012)
52. Scholz, C., Atzmueller, M., Barrat, A., Cattuto, C., Stumme, G.: New Insights and Methods For Predicting Face-To-Face Contacts. In: Proc. 7th Intl. AAAI Conference on Weblogs and Social Media. AAAI Press, Palo Alto, CA, USA (2013)
53. Scholz, C., Doerfel, S., Atzmueller, M., Hotho, A., Stumme, G.: Resource-Aware On-Line RFID Localization Using Proximity Data. In: Proc. ECML/PKDD. pp. 129–144. Springer, Heidelberg, Germany (2011)
54. Simmel, G.: The Sociology of Georg Simmel, vol. 92892. Simon and Schuster (1950)
55. Strogatz, S.H.: Exploring Complex Networks. nature 410(6825), 268 (2001)
56. Tichy, N.M., Tushman, M.L., Fombrun, C.: Social Network Analysis for Organizations. Academy of management review 4(4), 507–519 (1979)
57. Turner, J.C.: Towards a Cognitive Redefinition of the Social Group. Cahiers de Psychologie Cognitive 1(2), 93–118 (1981)
58. Veenhoven, R.: Sociological Theories of Subjective Well-Being. The Science of Subjective Well-being: A tribute to Ed Diener pp. 44–61 (2008)
59. Wasserman, S., Faust, K.: Social Network Analysis: Methods and Applications. No. 8 in Structural Analysis in the Social Sciences, Cambridge University Press, 1 edn. (1994)
60. Wu, L., Waber, B.N., Aral, S., Brynjolfsson, E., Pentland, A.: Mining Face-to-Face Interaction Networks using Sociometric Badges: Predicting Productivity in an IT Configuration Task. SSRN 1130251 (2008), Working Paper Series