Visualizing Informal Learning Behavior from Conference Participants' Twitter Data with the Ostinato Model

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ABSTRACT

Network analysis is a valuable method for investigating and mapping the phenomena that drive the social structure and for sharing the findings with others. This article contributes to an emerging field of 'smart data' research on Twitter by presenting a case study of how community managers in Finland used this social media platform to construct an informal learning environment around an annually organized conference. In this empirical study we explore informal learning behavior in the project context, especially by analyzing and visualizing informal learning behavior from Twitter data using the Ostinato Model introduced in this paper. Ostinato is an iterative, user-centric, process-automated model for data-driven visual network analytics.

Keywords

Learning, informal learning, memory aids, communities of practice, social network analysis, visual network analytics, Twitter.

1. INTRODUCTION

Learning is a mechanism for people, groups, industries and society to benefit / gain knowledge from past experiences, adapt to the context of any given situation, and to facilitate change. Interest in learning has grown in companies, especially since managers have responded to the knowledge economy (Drucker, 1994) and its prime importance for creating and sustaining competitive advantage (Alavi & Leidner, 2001; Choo, 1996; Grant, 1996; Nonaka & Takeuchi, 1995). However, academic research into informal learning in this regard is in its infancy. Therefore, this paper seeks to understand the informal learning of communities of practice through the utilization of 'smart data' (e.g. Patil, 2012) captured via social media. The following paper uses Twitter data to analyze the behavior of participants prior to attending a professional conference. The paper does this in order to understand informal learning before a conference event so as to be able to anticipate conference participant behavior.

Our aims are to find out what the community of "community managers" discussed before a yearly face-to-face event, in order to provide insights into what the most popular discussions of the community are in general and in relation to the conference event, and what kind of sub-groups and networks can be identified from the community in order to make propositions on the role of social media as an informal and non-formal learning environment.

In the theoretical section of this article, we introduce the concepts of informal and formal learning, internal and external memory aids and the context of communities of practice as informal learning environments. The Ostinato model data-driven approach allows investigations of patterns and structures within and between groups of actors. It can be extended beyond the boundaries of individual social media and cover long periods of time. Actors with different sets of skills, from the means to crawl online sources for data to domain knowledge allowing deep sense-making, can all fully engage in the different phases of the investigative process (Huhtamäki, Russell, Rubens, & Still, 2015).

These contributions allow the use of visual representations of the structures behind various social media phenomena to improve social interaction, in this article informal learning behavior in particular. In the empirical part of this article, we discuss Twitter as an informal learning environment and the social network analysis model, the Ostinato. We introduce a visualization of the hashtag metrics of people tweeting during the two weeks before the CMAD 2014 conference day. Finally, we conclude by demonstrating and discussing the use of social media as mediator in informal learning when building up to an organized event.

2. THEORY AND RELATED RESEARCH

2.1 Learning Forms and Mechanisms

The ability to learn faster than competitors is a sustainable form of competitive advantage for companies. In our dynamic contemporary world, there is a growing need to solve the problems at hand by continuously improving knowledge and skills in the face of changing conditions and situations. This means that learning has emerged as an important activity for individuals, communities, and companies. Learning can appear in various forms. We need to identify different types of learning in order to be able to create and nurture fertile learning environments.

There are three categories of learning in firms: informal, formal, and non-formal learning. Raivola and Ropo (1991) considered informal learning to constitute all that is related to the work process itself, including the carrying out of the work. During a work process, new things are learned that affect the work processes in one way or another, either directly or indirectly. Informal learning is often not noticed or realized. Therefore, it can be called tacit knowledge and know-how accumulation (Aramo-Immonen, Koskinen, & Porkka, 2011). Tacit knowledge and know-how accumulation are crucially important for the professional identity and go beyond taught formal qualifications. Finally, non-formal learning is understood as taking place outside the daily routines of the workplace or school.

García-Peñalvo, Colomo-Palacios and Lytras (2012) maintained that informal learners usually have their own learning goals and learn when they feel a need to know. Learning is demonstrated to the learner by their ability to carry out and achieve something that previously they had been unable to do. Informal learning can be seen as often being a combination of small chunks of observing how others do things, asking questions, trial and error, sharing stories with others, and casual conversations. (García-Peñalvo et al., 2012)

According to Sarala (1993), small team activity is a means towards company-based learning. The efficiency of working life today is increasingly based on the smooth and innovative collaboration of parties (such as in projects, events and conferences) that work together. It can relate to both teams and individuals and does not only apply to whole organizations. Monetary incentives (e.g. bonuses) are often connected to results, calling for an increased need to develop one's own work. In the case of voluntary work in events or not-for-profit work in conferences, financial gain cannot be the motivator. A person must gain something non-financial from being part of the community, for example. This paper looks at the not-for-profit work associated with organizing, attending, and engaging with a conference. An operating system – conference committees in our case - can only be efficient if its parts are efficient. This calls for collaboration, planning, and realization of the operation in virtual teams. For this purpose various learning environments are crucial. The development of creativity and increased utilization of Twitter for example, is evidence of an emerging new learning environment, namely social media platforms. These act as a new form of knowledge sharing arena (Nonaka & Takeuchi, 1995).

In comparison to the learning that takes place in functional organizations and is systematic, singular events and non-repeating project activities (such as focal conference preparations) provide little scope for routine learning (Hobday, 2000) or systematic repetition (Gann & Salter, 2000). The problem with this perspective on project-based learning is that it suggests that project-based activities are non-routine. Davies and Brady (2000) argue that performance and learning can be increased in companies that undertake 'similar' categories of projects in nature or new product markets. These 'similarities' can be exploited for learning by understanding the repeatable and predictable patterns of activities. Furthermore, conferences and events, even though they are unique, also have repeatable patterns of activity and structure and organization (Aramo-Immonen, Jussila, & Huhtamäki, 2014).

The perception that conferences and events perform only unique and non-routine tasks often masks transferable lessons that can be learned. DeFilippi & Arthur (2002) argued that these can occur at several different levels, e.g., individual, project, and company. Many firms have tried to create learning mechanisms to purposefully try to capture the experience gained through projects (Prencipe & Tell, 2001; Aramo-Immonen, 2009). These mechanisms refer to the institutionalized, structural, and procedural arrangements that allow companies to systematically collect, analyze, store, disseminate, and use knowledge (Popper & Lipshitz, 1998; Aramo-Immonen, 2009). Conferences can relate to an organization and utilize the corporate mechanism to learn from the event, but they also exist beyond the individual person or company, obtaining an agency in their own right. This can result in their own momentum leading to the pursuit of new objectives, enabling the possibility to learn within the parameters set for the conference itself (Aramo-Immonen et al., 2014).

2.2 External Memory Aids

Koskinen and Aramo-Immonen (2008) studied the utilization of an engineer's personal notes in problem-solving situations within the implementation of projects. They found that note-taking and the utilization of these notes are common practices in the context of a project. In particular, they found that people working in a project work context consider that their personal notes play a very important role on an individual level and a fairly important role on a project level. Moreover, knowledge hoarding is more uncommon a phenomenon in a project work context than is often reported in functional organizations. Furthermore, the understanding of colleagues' notes often requires help from the knowledge makers. It was concluded that the personal notes of project team members' form a significant part of project-based companies' organizational memories (Koskinen & Aramo-Immonen, 2008).

External memory aids come in many forms, e.g., taking notes in a meeting, entering an appointment in a calendar, photographs, drawings, maps and the like (Intons-Peterson & Newsome III, 1992). Additionally, asking someone else is also used as an external memory aid. This means that external memory aids are used to retrieve memories from the past. The use of external memory aids to facilitate remembering in the future is a very common technique, for example, people writing notes in a diary. Some external memory aids are distinctly verbal in nature, encompassing either oral (e.g. conversations with others) or written functionality (e.g., reminder notes, calendar entries), while others are more spatial (e.g., pictures, maps, sketchnotes). (Koskinen & Aramo-Immonen, 2008). Rich pictures, as an example of spatial memory aid, were developed as part of Peter Checkland's Soft Systems Methodology for gathering information about a complex situation (Checkland, 1981; Checkland & Scholes, 1990). In the context of social media, photographs are an example of another spatial memory aid. These memory aids have a special role as a mediator of knowledge as "one picture tells more than one thousand words".

The Teaching Research Institute (2011) of Western Oregon University maintained that external memory aids fall into two categories: "low tech" and "high tech." Low-tech aids include pencil/paper systems and simple organization tools: checklist, calendars, notebooks, and daily planners, etc. High-tech aids include electronic devices that have a range of programming options: digital voice recorders, programmable watches, PDAs (personal digital assistant), "pocket computers", IPod Touch, cell phones (mobile phones and smartphones), etc. (Teaching Research Institute, 2011). It is proposed that social media platforms like Twitter also fall within this high-tech category.

In order to remember something, people commonly rely on low tech methods, placing reminders in different places or following their calendars (Meacham & Leiman, 1982). However, repositories like these are not only used as an aid but they can often be the central storage areas for large amounts of knowledge that cannot be retrieved elsewhere (Koskinen & Aramo-Immonen, 2008) in that the central repositories can only truly be retrieved by the originator of the memory aid, or at least the originator's involvement is required in some capacity to decipher the memory aid. Recently, however, high tech methods like social media have begun to act as a common memory aid shared by communities. The scrawls an individual project team member makes in a diary may become the only record of many solutions made in a project and the decision pathways chosen by the team. In contrast, discussion in a shared community such as Twitter for example functions as a collaborative memory aid. When an individual is not able to reconstruct a problem solution without reference to a diary, the diary often provides reminders. Thus, through the creation of personal notes, it is possible to make an individual less vulnerable to loss of knowledge about problem solutions and, by sharing these notes on social media (e.g. Twitter, Facebook, Google Drive, Evernote), individuals can form shared knowledge with others. Furthermore, certain individuals can take different roles based on their unique skill sets, like sketching conference plans or presentations as sketchnotes and sharing them on Twitter for the benefit of all attendees (Jussila, Huhtamäki, Henttonen, Kärkkäinen, & Still, 2014). Thus social media forms the base for a new kind of collaborative knowledge creation (Jussila, Kärkkäinen, & Leino, 2012; Merigó, Rocha, & Garcia-Agreda, 2013) that takes advantage of networks in creating value by solving problems that exceed the capacities of one professional (Schultze & Stabell, 2004).

2.3 Transactive Memory

The capability of groups to encode, store, and retrieve knowledge, through the use of a group memory system called the transactive memory (TM), has been found in many studies to be superior to that of individuals (e.g. Wegner, 1995). TM and transactive memory systems (TMS) have drawn the attention of many researchers because they are able to facilitate the understanding of knowledge use and coordination among groups of people, and have been found to be significant in performance development of ad-hoc groups (Schreiber & Engelmann, 2010), and among other group types. In TM, individual memory systems are fused together, thus forming collective information processing systems, which provide individual members of the system with access to a knowledge base more complex, varied and potentially more effective than each member individually would possess (Wegner, 1987). TM can be seen as important for the efficiency of formal and informal types of learning alike, which can make use of various groups of people for learning purposes. These ad-hoc groups also include social media or Twitter-based communities. The roles of building TM through social media need to be further empirically explored in the academic literature, even though the potential of social media has been recently realized in TM development, e.g. in the context of travel information (Chung, Lee, & Han, 2015).

Some important components of building transactive memory and related TM systems concern getting to know who knows what and sharing this knowledge among group members. The transactive memory theory suggests a shared group "directory," enabling members to efficiently retrieve and share knowledge. This directory can be conceptualized as a shared understanding of individual expertise. Furthermore, group members have to start specializing their knowledge and knowledge sharing accordingly.

2.4 Informal Learning through Community of Practice

Communities of practice arise in response to a common interest or viewpoint, and have been described as "a collection of people who engage on an ongoing basis in some common endeavor." (Eckert, 2006, p. 1). Similarly, Wenger et al. (2002, p. 7) define communities of practice as "groups of people who share a concern, a set of problems, or a passion about a topic, and who deepen their knowledge and expertise in this area by interacting on an ongoing basis." They enable their members to be involved with and influenced by their social context, which provides an accountable link between the individual and the world around them. It also provides a context in which linguistic articulation is integral to this link (Eckert, 2006).

The concept of communities of practice has been directly linked to organizational learning (Lave & Wenger, 1991; Wenger, 1998; Wenger et al., 2002). In their opinion, organizations consist of communities of practice, and so, if organizational learning is to occur, then learning in communities needs to be encouraged (Ropes, 2010). The idea is similar to that of Nonaka and Takeuchi (1995), who suggested that knowledge sharing arenas are vital for organizational learning. We suggest that social media platforms function as knowledge sharing arenas for a community of practice. Wenger (1998, p. 5) purported that learning is a continual social process that has four interdependent and intertwined elements (meaning, practice, community, and identity). Furthermore, Wenger et al. (2002) went on to describe seven principles for activating communities of practice. These principles, paraphrased below, are particularly applicable when understanding the formation and development of communities of practice leading up to an event.

Design for evolution: Shepherding the organic evolution of the community of practice.

Open a dialogue between inside and outside perspectives: An insider's perspective to lead the discovery of what the community is about, and an outside perspective to help members see the possibilities.

Invite different levels of participation: Good community architecture invites many different levels of participation - coordinators, active leaders but also members on the periphery who rarely participate. To draw members into more active participation, successful communities build a fire in the center of the community that will draw people to its heat.

Develop both public and private community spaces: Like a local neighborhood, dynamic communities are rich with connections that happen both in the public places of the community - meetings, website - and the private space - the one-on-one networking of community members. The public and private dimensions of a community are interrelated, and require orchestration applicable to both.

Focus on value: Communities thrive because they deliver value to the organization, to the teams on which community members serve, and to the community members themselves.

Combine familiarity and excitement: Lively communities combine both familiar and exciting events, so community members can develop the relationships they need to be well connected as well as generate the excitement they need to be fully engaged.

Creating a rhythm for the community: The rhythm of the community is the strongest indicator of its aliveness, and finding the right rhythm at each stage is key to a community's development.

The sense-making that occurs with communities of practice relies on two conditions being met, namely shared experience over time (evolution), and commitment to shared comprehension (Eckert, 2006). Therefore, a community of practice through the medium of social media nurtures an informal learning environment that both enhances a shared understanding, and evolves over time. That evolution is particularly important for this paper as we seek to understand informal learning in communities of practice over a timespan leading up to an event (CMAD 2014).

2.5 Informal Learning through Twitter

Grudz, Wellman, & Takhteyev (2011) maintained that Twitter, unlike social network sites such as Facebook or LinkedIn, was not intended primarily as a platform for building communities, instead it was designed to be a tool for information dissemination. However, there is a growing area of research that has examined the development and possibilities of communities that are formed on Twitter (Erickson, 2008; Gruzd et al., 2011; Huberman, Romero, & Wu, 2008; Java, Song, Finin, & Tseng, 2007; Loureiro-Koechlin & Butcher, 2013; Zappavigna, 2012; Stephansen & Couldry, 2014). Moreover, there is a growing trend of academic literature on the use of Twitter in formal learning, focusing on the effectiveness of Twitter as a tool for formal learning processes, for example to improve linguistic competency (Cano, 2012), memory of concepts (Blessing, Blessing, & Fleck, 2012), and to support large-lecture courses (Elavsky, Mislan, & Elavsky, 2011) and massive open online courses (García-Peñalvo, Cruz-Benito, Borrás-Gené, & Blanco, 2015; J Cruz-Benito, Borrás-Gené, García-Peñalvo, Fidalgo Blanco, & Therón, 2015). Although there are some notable examples of academic research that have explored the use of Twitter in informal learning processes and social relationships (e.g. Ebner, Lienhardt, Rohs, & Meyer, 2010; Junco, Heiberger, & Loken, 2011; Junco, Elavsky, & Heiberger, 2013; Kassens-Noor, 2012; Dabbagh & Kitsantas, 2012; Stephansen & Couldry, 2014), these studies have focused on the school environment, e.g. the college or university context, whilst informal learning in communities of practice and the project work context has not received the same level of academic consideration.

This article contributes to this emerging field of research on informal learning in communities of practice and the project work context by presenting a detailed case study of how community managers from various organizations in Finland have used Twitter to construct an informal learning environment. In particular, it explores informal learning activity by community managers prior to a conference event.

3. RESEARCH APPROACH

3.1 Research Method

In this study, we follow the data science research approach (e.g. Hey, Tansley, & Tolle, 2009) and apply the process of data-driven visual network analytics (Card, Mackinlay, & Shneiderman, 1999) and the Ostinato process model (J. Huhtamäki et al., 2015) to provide insights into the informal learning of a community of *community managers* based on Twitter data retrieved two weeks before the CMAD 2014 conference. As Twitter can be seen to represent an information system, we utilize the case study method, which has been found to be a legitimate way of adding to the body of knowledge in the information systems field; it provides detailed and analyzed information about real world environments through examples of the phenomena under research (Benbasat, Goldstein, & Mead, 1987).

3.2 Case CMAD 2014

The informal learning environment in our case is the online discussions of community managers in the social media, especially on Twitter (#cmadfi), in connection with the annual Community Manager Appreciation Day (CMAD 2014) event in Finland. The most recent event took place on January 27, 2014 in Hämeenlinna, Finland. CMAD events have been organized globally since 2010 and they originate from Jeremiah Owyang's blog to recognize and celebrate the efforts of community managers around the world using social media and other tools to improve customer experiences. The organizing committee of the third CMAD event (CMAD 2014) in Finland included more than 200 people, with 23 people participating in the planning meetings. A total of 225 people participated in the CMAD 2014 event.

It can be argued that discussions in the social media represent only a small or a very small part of the overall communication between community members in professional communities and their informal learning, because many professionals either do not have a Twitter account or are not active on Twitter. As a consequence, data science approaches can be seen as of limited use in studying professional communities. In this case, however, the majority of the members belonging to the community of *community managers* can be considered as advanced lead users of social media and online community management approaches, with most of them being highly active on Twitter. Second, in relation to learning events and conferences, it has been observed that most of the activity takes place during the learning event or conference itself, with little communication before and after (Ebner & Reinhardt, 2009), making it questionable to draw legitimate conclusions from data collected two weeks before the conference. We agree that by collecting data before, during, and after the conference using the hashtag (e.g. #cmadfi) of the conference (see e.g. Jussila et al., 2014), this is usually the case. However, based on previous studies of community managers in Finland (Jussila, Huhtamäki, Kärkkäinen, & Still, 2013; Jussila et al., 2014), we would argue that community managers communicate with each other between events, and have also participated actively in planning the event, and assume that by collecting data based on all the discussions of these community members (not only using the #cmadfi hashtag), we can capture a sufficient and representative amount of data from which to draw conclusions.

3.3 Data Science Research Approach

Data science has been used as a general term to refer to a wide set of skills and practices required to operate in the big data sphere (e.g. Davenport, 2014), and also to refer to the fourth paradigm for science (Hey et al., 2009). From a research viewpoint, the scientific approach in in-built, quantitative analysis is a core methodology, and business researchers seek to answer the questions that are of interest to business. Data science does, however, highlight two areas that can benefit state-of-the-art research. First, applying novel approaches in collecting data from online sources, referred to by Davenport (2014) as hacking, allows the use of a new kind of data in research. Second, the use of information visualization and other means of presenting the results of the analysis coupled with storytelling practices aims to increase the impact of analysis. According to Ware (2004), information visualization can amplify the cognition of the user through expressive views, thus providing insight on the phenomena represented by the data. Overall, the process of data analysis "covers a whole range of activities throughout the workflow pipeline including the use of databases (versus a collection of flat files that a database can access), analysis and modeling, and then data visualization." (Hey et al., 2009). Previous related studies on information visualization and visual analysis that have been conducted in connection to eLearning following a similar research approach include for example (Gomez-Aguilar, Conde-Gonzalez, Theron, & Garcia-Peñalvo, 2011; Tervakari et al., 2012; Silius, Tervakari, & Kailanto, 2013; D. A. Gómez-Aguilar, Therón, & García Peñalvo, 2013; D.-A. Gómez-Aguilar, García-Peñalvo, & Therón, 2014; Juan Cruz-Benito, Therón, García-Peñalvo, & Lucas, 2015).

3.4 Sense-making via the Ostinato Model

In the context of this study, the Ostinato Model is used to conduct the study with a data-science mindset. The Ostinato Model is an iterative, user-centric, process-automated model for data-driven visual network analytics designed to support the automation of the process while maintaining the option for interactive and transparent exploration for investigators independent of their technical skills (J. Huhtamäki et al., 2015).

Visual network analytics refers to taking a visual analytics (Thomas & Cook, 2006; Heer & Shneiderman, 2012) approach to network analysis. Visual network analytics allows the emergence of insights on the structure and dynamics of innovation ecosystems, social media platforms and other networked phenomena. Existing research on networks shows that network analysis has a good fit for explorative analysis of social media: much is already known about the structure in networks (Granovetter, 1973; Barabási & Bonabeau, 2003), the roles of individual actors in the network (D. Hansen, Shneiderman, & Smith, 2010), the drivers of network evolution (Giuliani & Bell, 2008) as well as the latent structures and dynamics behind the diffusion of information through networks (Leskovec, Backstrom, & Kleinberg, 2009), network control (Liu, Slotine, & Barabási, 2011), and virality (Shakarian, Eyre, & Paulo, 2013; Weng, Menczer, & Ahn, 2013). In short, visual network analysis is a valuable method for investigating social configurations and for interactively communicating findings to others (cf. Freeman, 2009).

Data-driven visual network analytics leverages computation to analyze potentially very large datasets in order to identify the patterns driving complex phenomena. Moreno (1953), Freeman (2000), Hansen et al. (2009; 2010), Russell et al. (2011; 2015), Still et al. (2014), Basole et al. (2012), Ritala and Hallikas (2011), and Ritala and Huizingh (2014) give examples of using a network approach to investigate complex phenomena that are driven by sets of interconnected actors. To implement data-driven processes, processes composed of crawlers and scrapers for collecting data as well as components for refining and transforming the data need to be developed. Especially in cases involving data that are heterogeneous by nature, an iterative, incremental analysis process is sometimes necessary (Telea, 2014).

Analysis of complex phenomena often involves multiple pathways to actionable recommendations, and the assumptions underlying decisions may change over time. In order to keep the data-driven process transparent and accessible to all the stakeholders involved with a particular investigation, raw data as well as different intermediate representations of the data have to be made available to all the members of the investigative team. (Huhtamäki et al., 2015).

While information visualization in the Ostinato Model includes data transformation, representation, and interaction, it is ultimately about harnessing human visual perception capabilities to help identify trends, patterns, and outliers. Sense-making has its roots in cognitive psychology and many different models have been developed. Sense-making procedures are cyclic and interactive, involving both discovery and creation (North, 2006). During the data collection and refinement phase, an individual searches for representations. In the network generation phase, these representations are instantiated, and based on these insights the representation may be shifted, to begin the process again. Sense-making is closely linked to the insight objectives (Konno, Nonaka, & Ogilvy, 2014), and the Ostinato cycle of exploration–automation is key in achieving actionable insights that network orchestrators can utilize. (Huhtamäki et al., 2015).

When sense-making requirements have been satisfied for investigators and users, the steps of the Ostinato process can be formalized with automated procedures for iteration over time. The key actors, relationships, and events of the network can be incorporated into dashboards that will track changes in critical assumptions and into stories that will share a vision for actionable change. (Huhtamäki et al., 2015).

In the following sections, we describe how the two phases of the Ostinato Model, i.e. Data Collection and Refinement, and Network Creation and Analysis, were implemented in this study.

The study-specific process was developed over an iterative cycle of exploration and automation.

3.4.1 Collection and Refinement of Social Media Data

The Data Collection and Refinement phase is composed of Entity Index Creation, Web/API Crawling, Scraping, and Data Aggregation. A pre-existing Twitter list put together by Marko Suomi including all the conference participants[1] was used as the entity index. The crawling process to collect the data was implemented as a tailored batch script in Python. The script accessed Twitter REST API periodically over the two-week period before the conference to make sure that all the tweets were captured. Twitter API serves the data in JSON (Javascript Object Notation), a format designed for machines to process, therefore making data scraping superfluous. The data originated from an individual source, thus no aggregation was needed. Twitter REST API was sufficient for collecting the tweets for the event because it allows the retrieval of 1500 tweets at a time, 350 times an hour. Investigations that look into Twitter streams with larger volume insist on applying the Twitter Streaming API instead of the REST API.

3.4.2 Network Construction and Analysis

First, source data is collected and stored into a local database, a proxy that significantly speeds up the subsequent processing steps. Second, names of entities to be used as network nodes, here actors and hashtags, are refined in the proxy to ensure their consistency. With Twitter data, this is straightforward as the only variation in actor names and hashtags is caused by uppercase and lowercase letters. Here, we transform all the names to lowercase letters. Next, network can be constructed and analyzed.

The Network Construction and Analysis phase of the Ostinato Model is composed of Filtering in Entities, Node and Edge Creation, Metrics Calculation, Node and Edge Filtering, Entity Index Refinement, Layout Processing, and Visual Properties Configuration.

For this study, several network representations were created from the data, with individual tweeters and hashtags represented as nodes connected through tweeters mentioning each other as well as tweeters using hashtags. Node indegree was used to help in pinpointing the most prestigious actors that others refer to the most. Node betweenness was selected to investigate the actors and hashtags that act as brokers, bridging the structural holes in the networks representing CMADFI 2014. In this case, however, the networks are very dense, therefore no major structural holes exist.

Network construction processes for this study were implemented in Python using the NetworkX library. To analyze the networks, we extensively utilized Gephi[2], an interactive network visualization and exploration platform (Bastian, Heymann, & Jacomy, 2009). Gephi allows the laying out of networks with different algorithms, calculating different node-level metrics, as well as filtering nodes and edges according to their properties as well as calculated metrics. Gephi further allows time-based network filtering as well as animating the evolution of the network for insights on user behavior on system level. Particularly, node and edge filtering was applied when conducting the investigations. Moreover, due to space limitations, for the hashtag co-occurrence network we filtered in only the giant component of the co-occurrence network.

To complement visual network analytics with scatterplots and timelines, we applied Tableau, a commercial state-of-the-art business intelligence and analytics tool that allows exploration of the data in an agile manner.

4. RESULTS AND FINDINGS

We identified, selected, and performed different quantitative and qualitative visualization-backed analyses using the Twitter data collected before the conference to understand the possibilities of Twitter and visualizations for supporting informal learning. To do this, we selected several visualization approaches, partly also by experimenting with different visualizations, especially related to the following issues that are related to the facilitation of informal learning:

i) Understanding the volume of different main discussion topics in timeline before the conference (identifying an overview of conference participant activity; identifying both more formal professionally oriented learning topics and informal topics helping e.g. to get acquainted with each other and each other's interests).

ii) Discovering the most popular broader discussion topics and individual discussions of community managers (e.g. helping to set own goals for learning).

iii) Identification of discussion topics and their relations to each other (e.g. understanding broader themes related to own interests).

iv) Identifying which subgroups of people and individual persons are interested in certain topics (e.g. identifying whom to contact before or during conference).

4.1 Quantitative and qualitative analyses of Twitter data

In order to get an overview of user activity, we created a timeline of the volume of different hashtags before the conference (Figure 1). The timeline of hashtags reveals two main peaks of activity. First, many of the participants joined discussions on two popular TV shows, Comedy Combat (Putous) and New Music Competition (Uuden Musiikin Kilpailu, UMK), that were aired during the same time. The largest peak of activity took place during the Digitalist Marketing Forum (#digitalist, #dmf) event.

CMADFI-related hashtags, #some (social media) and #KM (for knowledge management), for example, are more evenly distributed on the timeline.

[1] https://twitter.com/markosuomi/lists/cmadfi2014

[2] http://gephi.github.io/

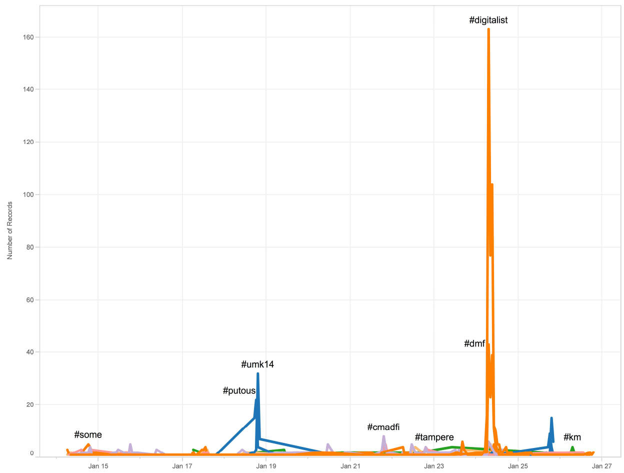

Figure 1. Top hashtags over time before the conference.

In order to discover the most popular discussions of community managers from a time period of two weeks before the conference day, a hashtag table was constructed (Table 1). The table enables interactive sorting by hashtag name, volume, number of related hashtags, and related hashtags. Sorting by volume in descending order quickly reveals the most popular topics and related sub-topics of discussions by community managers. It not only reveals what was discussed about the CMAD 2014 conference (#cmadfi), but also other events the community managers had participated in, either face to face or online, such as digitalist, dmf, and slush events. The top five discussion topics also point to specific subject area interests, such as social media and recruitment.

Table 1. Top 5 hashtags that CMAD 2014 participants used during the two weeks before the conference day. An interactive version is available at: http://bit.ly/chashtags

Name	Vol.	No. of Related Hashtags	Related Hashtags
Digitalist	410	102	Cmadfi, dmf, customerservice, marketing, some, recruitment, …
Dmf	122	24	Customerservice, digitalist, service, marketing, …
Cmadfi	117	28	Cmad, digitalist, communitymanager, communities, cmgr, cmadride, cmadbus, some, slush13, recruitment, …
#umk14	77	13	Hipster, MikkoPohjola, Madcraft, Resultshow, YLE, …
Recruitment	70	55	Cmadfi, digitalist, coaching, jobs, career, worklife, …

The table does not, however, give a good overview of the discussions. More specifically, an investigator is not able to observe which kinds of discussions are most related to each other, and what kinds of issues are most interrelated. For this purpose, a second visualization was constructed to display the co-occurrence of hashtags in matrix form. In the matrix view, the discussions are clustered based on the choice of sorting parameter: volume, partition, and total number of co-occurring tweets (Cherny, 2012). Observed from the co-occurrence of the hashtags matrix, and sorted by partition, 7 larger partitions were identified, representing 7 different sub-groups of discussions inside the community of community managers. In Figure 2, the different partitions (clusters) can be identified by different colors; some partitions are denser (e.g. the first partition) and some more scattered (e.g. the second partition). See the interactive version of Figure 2 for more details. The partitions included a range of related discussion topics and, based on the content, these can be categorized into the following: 1) travel (blue cluster); 2) jobs, career and human relations (orange cluster); 3) CMAD 2014 event (1st purple cluster); 4) social media (green cluster), 5) sales (red cluster); 6) entrepreneurship and education (pink cluster), learning and teaching (2nd green cluster); 7) Digitalist (2nd purple cluster).

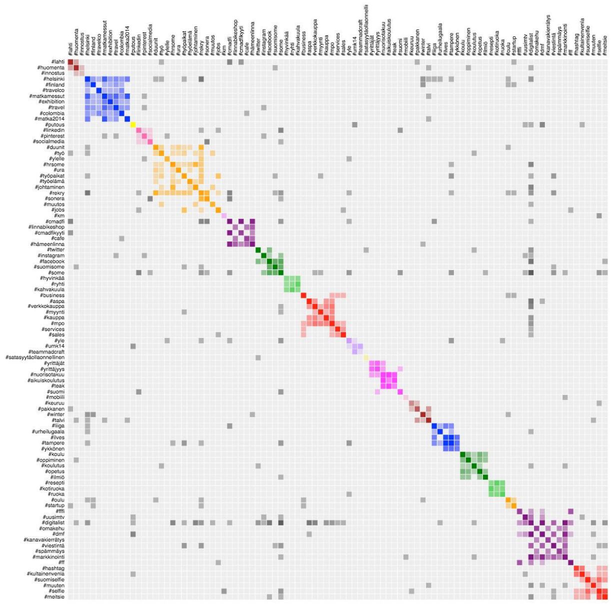

Figure 2. Hashtag metrics of people tweeting during the two weeks preceding the CMAD 2014 conference day. Interactive visualization available at: http://bit.ly/cmadfi-hcmatrix.

To provide an overview of the discussions that took place before the CMAD 2014 conference day, we created two additional visualizations, a network of hashtag co-occurrences, and a two-mode network of CMADFI participants tweeting and the hashtags they used.

The network of hashtag co-occurrences (Figure 3) enables the identification of discussion topics and their relations to each other. In the interactive visualization, each node can be selected and the corresponding connections become visible. Figure 3 shows an example of the central node CMAD 2014 (cmadfi) and the discussions most related to it. Logistics was discussed most, as can be expected of pre-conference discussions. In other words, how to get to the conference venue, e.g. by organizing shared transportation. Communities (yhteisöt), community managers (yhteisömanagerit) and building a sense of community (yhteisöllisyys) were discussed the second most. Third most discussed were social media (some), and recruitment (rekry). The interactive visualization also makes it possible to see what, if any, the connections between any two nodes are. For example, when selecting CMAD 2014 and Digitalist Marketing Forum it can be observed that social media (some) is the strongest connection between these two nodes.

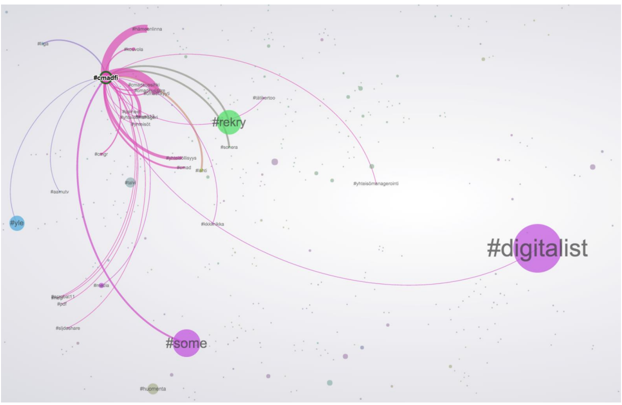

Figure 3. Interactive visualization of hashtag co-occurrences during the two weeks before the conference day. Interactive visualization available at: http://bit.ly/cmadfi-hcnetwork.

In concert, these two former visualizations help to organize and facilitate discussions and networking events for the actual conference on themes that the community managers perceive to be important, for example social media and recruitment. They do not, however, reveal who is talking about what. To understand which sub-groups are interested in certain topics, e.g. social media (some) and social media in recruitment (rekry), other kinds of visualizations are needed. For this purpose, an interactive social network of people and hashtags was constructed (Figure 4).

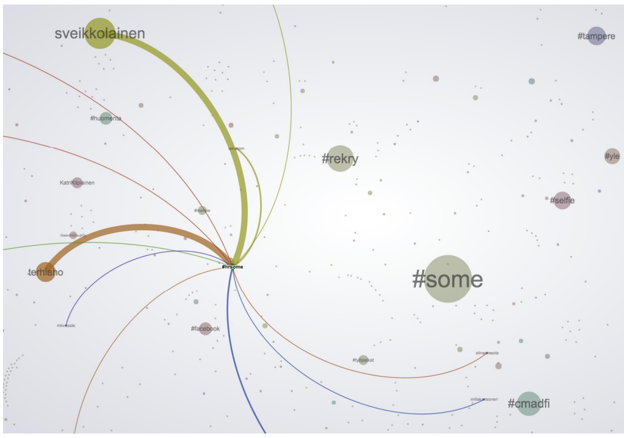

Figure 4. Interactive visualization of people tweeting and their hashtags during the two weeks before the conference day. Interactive visualization available at: http://bit.ly/cmadfi-tmnetwork.

The interactive visualization of people and hashtags enables the investigator to look at specific nodes, e.g. one can look at a specific node representing a person, and see which other people are discussing with this node and to which discussion topics this node is related. Conversely, you can look at a specific hashtag node (e.g. social media in human relationships, hrsome) and see which people are talking about the topic and what other topics are related to the topic.

Figure 4 can be used to find people with similar interests to network with and share knowledge with even before the conference. For the organizers, Figure 4 gives clues about which people should be seated at the same tables at lunch for example to generate fruitful further discussions for informal learning.

5. DISCUSSION

Network analyses and visualizations of Twitter data backed up with a process implementation following the Ostinato Model can be used to partly automate the creation process of an event-specific (here conference) learning environment, and to support informal learning in various ways. Alterations to a learning environment content or structure can be made quickly as the understanding of the requirements for the learning environment improves over time through visualization-driven feedback (Huhtamäki, Nykänen, & Salonen, 2009).

Based on findings from Twitter data visualization, we propose the following:

Proposition 1: Twitter combined with the visualization of Twitter data can help informal learners to set their personal learning objectives.

Informal learners usually set their own learning targets as they learn when they feel a need to know more about a given topic. Our study demonstrates that Twitter combined with Twitter data visualizations can help informal learners. It can enable them to discover themes that they already consider important to them, and can be learned from individually identified conference participants, or can raise new sub-themes or other related themes that they are currently interested in. These are demonstrated in the interactive visualizations of Table 1, which can be used to identify the conference topics ("Vol.") most commonly tweeted about by their Twitter volumes. Participants can also identify commonly discussed themes or themes discussed commonly in their context ("Related hashtags"), for instance in the context of the 6th most popular topic "Some," the themes of "Recruitment" and "Community management" were also popular. Furthermore, making use of the interactive matrix visualization of Figure 2, themes co-occurring in discussions can be identified. These co-occurring themes can trigger new learning objectives on a topic that a person was not previously aware of, for instance, in the "Some" theme; sub-themes such as "Instagram" can trigger a learning objective on how to use Instagram in content marketing. The visualization in Figure 4 also contains a search function which can be used to identify persons or topics related to a certain hashtag to enable further virtual or face-to-face discussions for identifying in more detail or validating ideas for personal learning objectives. These learning goals can, of course, also contain partly a plan whereby persons meet to facilitate learning during a conference. For example, the discussion concerning transportation was about the arrangements of communal bus transportation for conference attendees. This also facilitated face-to-face interaction before conference discussions. This, in turn, facilitated the possibility of informal learning during the shared journey.

Proposition 2: Visualizations of Twitter data can be used to facilitate and automate the development of the transactive memory for conference participants, enabling efficient informal learning.

The major components of TM are to know who knows what, and to share this knowledge among group members.Twitter data combined with SNA visualizations were found to enable the building of TM in several ways: First, they enable conference participants to discover persons with similar learning interests for informal learning. For the purpose of knowing who knows what, Twitter data alone does not provide a very in-depth picture in itself. Combining Twitter data with the interactive visualization of the names of people tweeting and the hashtags they have used before the conference (Figure 4) enables the easy discovery of people with knowledge on certain topics and all the related sub-topics, or persons with similar learning interests, which can help them to organize the informal learning tasks. Furthermore, by analyses of their Twitter links to others (incoming and outgoing) as well as analyses of re-tweets, persons can be discovered that are influential on certain topics that might be useful for them and their own informal learning purposes. The incoming links indicate their prestige and influence, while outgoing links indicate the activity of the people concerned. Discovering such persons makes it possible to create contacts before and during the conference in an efficient way, and to set up meetings with them, whilst discovering new personal contacts with similar knowledge for further learning. This can be difficult and time-consuming to do by traditional means. For example, people seeking a job regard participation in the community as a recruitment possibility.

Proposition 3: Informal virtual and physical learning environments can be built and supported based on information gained from the interactive visualization of people's behavior in a social network before a conference.

Based on the Twitter data accumulated before the conference and its visualizations, the building of informal virtual and physical learning environments can be efficiently supported. Themes that were of central interest for the participants were identified from hashtag clustering. Firstly, presentation themes and presenters were identified and selected to respond to their interests and learning objectives. Secondly, networking of participants was promoted by organizing common transportation and physical conference spaces and the related seating order, e.g. in the case of lunch tables and coffee tables, around the identified topics of interest. Thirdly, informal learning was supported by virtual discussions and the creation of ad-hoc groups around common topics of interest or informal learning tasks specific hashtags were designed and promoted, such as #cmadfikyyti to arrange transportation related issues and to network people before the conference. Fourthly, a social media platform (flockler.com), publicly available from cmad.fi, was used to serve as a collective knowledge repository, storing all the Twitter content before the conference, thus enhancing the learning of the participants.

An interesting new finding was the utilization of timeline and hashtag network visualization together. In addition to a timeline, the network visualization revealed additional topics of interest, e.g. recruitment, community management, and building a sense of community. These were less visible in the timeline because several different keywords were used for these topics, but network visualizations made them obvious. Consequently, analysing only the timeline or only the list of most common hashtags, one would miss important discussion themes concerning the event and of the interest of participants, whereas the network visualisations coherently groups themes together, such as recruiment and some.

In this paper, we enhance the understanding of how Twitter data, particularly combined with different types of network visualizations, can be used as a source for informal learning in ad-hoc types of social media-based communities in professional contexts.

6. REFERENCES

Alavi, M., & Leidner, D. E. (2001). Review: Knowledge Management and Knowledge Management Systems: Conceptual Foundations and Research Issues. *MIS Q.*, *25*(1), 107–136. http://doi.org/10.2307/3250961

Aramo-Immonen, H. (2009). Project management ontology-The organizational learning perspective. *Tampereen Teknillinen Yliopisto. Julkaisu-Tampere University of Technology. Publication; 836*. Retrieved from http://dspace.cc.tut.fi/dpub/handle/123456789/6495

Aramo-Immonen, H., Jussila, J., & Huhtamäki, J. (2014). Visualizing informal learning behavior from conference participants Twitter data. In *Proceedings of the Second International Conference on Technological Ecosystems for Enhancing Multiculturality* (pp. 603–610). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=2669962

Aramo-Immonen, H., Koskinen, K. U., & Porkka, P. L. (2011). The significance of formal training in project-based companies. *International Journal of Managing Projects in Business*, *4*(2), 257–273.

Barabási, A.-L., & Bonabeau, E. (2003). Scale-free. *Scientific American*. Retrieved from http://eaton.math.rpi.edu/csums/papers/FoodWebs/barabasisciam.pdf

Basole, R. C., Russell, M. G., Huhtamäki, J., & Rubens, N. (2012). Understanding Mobile Ecosystem Dynamics: a Data-Driven Approach. In *ICMB* (p. 15). Retrieved from http://aisel.aisnet.org/cgi/viewcontent.cgi?article=1014&context=icmb2012

Bastian, M., Heymann, S., & Jacomy, M. (2009). Gephi: An open source software for exploring and manipulating networks. In *International AAAI conference on weblogs and social media* (Vol. 2). Retrieved from http://www.aaai.org/ocs/index.php/ICWSM/09/paper/viewPDFInterstitial/154Forum/1009

Benbasat, I., Goldstein, D. K., & Mead, M. (1987). The case research strategy in studies of information systems. *MIS Quarterly*, 369–386.

Blessing, S. B., Blessing, J. S., & Fleck, B. K. (2012). Using Twitter to reinforce classroom concepts. *Teaching of Psychology*, *39*(4), 268–271.

Cano, E. V. (2012). Mobile learning with Twitter to improve linguistic competence at secondary schools. *New Educational Review*, *29*(3), 134–147.

Card, S. K., Mackinlay, J. D., & Shneiderman, B. (1999). *Readings in information visualization: using vision to think*. Morgan Kaufmann Pub. Retrieved from http://www.google.com/books?hl=fi&lr=&id=wdh2gqWfQmgC&oi=fnd&pg=PR13&dq=card+1999+information+visualisation&ots=olFC3zvJRs&sig=jSDLENOhswJwV1f5T_UIp4OvocM

Checkland, P. (1981). *Systems thinking, systems practice*. J. Wiley.

Checkland, P. B., & Scholes, J. (1990). *Soft systems methodology in action*. John Wiley & Sons Australia, Limited.

Cherny, L. (2012). Ghostweather R&D Blog: Digging Into NetworkX and D3. Retrieved March 11, 2015, from http://blogger.ghostweather.com/2012/03/digging-into-networkx-and-d3.html

Choo, C. W. (1996). The knowing organization: How organizations use information to construct meaning, create knowledge and make decisions. *International Journal of Information Management*, *16*(5), 329–340. http://doi.org/10.1016/0268-4012(96)00020-5

Chung, N., Lee, S., & Han, H. (2015). Understanding communication types on travel information sharing in social media: A transactive memory systems perspective. *Telematics and Informatics*, *32*(4), 564–575.

Cruz-Benito, J., Borrás-Gené, O., García-Peñalvo, F. J., Fidalgo Blanco, Á., & Therón, R. (2015). Extending MOOC ecosystems using web services and software architectures. In *In Proceedings of the Interacción 2015. XV International Conference on HCI (Villanova I la Geltrú, Spain. 2015)*. ACM.

Cruz-Benito, J., Therón, R., García-Peñalvo, F. J., & Lucas, E. P. (2015). Discovering usage behaviors and engagement in an Educational Virtual World. *Computers in Human Behavior*, *47*, 18–25.

Dabbagh, N., & Kitsantas, A. (2012). Personal Learning Environments, social media, and self-regulated learning: A natural formula for connecting formal and informal learning. *The Internet and Higher Education*, *15*(1), 3–8.

Davenport, T. (2014). *Big Data at Work: Dispelling the Myths, Uncovering the Opportunities*. Harvard Business Review Press.

Davies, A., & Brady, T. (2000). Organisational capabilities and learning in complex product systems: towards repeatable solutions. *Research Policy*, *29*(7), 931–953.

DeFilippi, R. J., & Arthur, M. B. (2002). Project-based learning, embedded learning contexts and the management of knowledge. *Research Paper, Suffolk University, Boston*.

Drucker, P. F. (1994). The age of social transformation. *The Atlantic Monthly*, 53–80.

Ebner, M., Lienhardt, C., Rohs, M., & Meyer, I. (2010). Microblogs in Higher Education–A chance to facilitate informal and process-oriented learning? *Computers & Education*, *55*(1), 92–100.

Ebner, M., & Reinhardt, W. (2009). Social networking in scientific conferences–Twitter as tool for strengthen a scientific community. In *Proceedings of the 1st International Workshop on Science* (Vol. 2, pp. 1–8).

Eckert, P. (2006). Communities of practice. *Encyclopedia of Language and Linguistics*, *2*, 683–685.

Elavsky, C. M., Mislan, C., & Elavsky, S. (2011). When talking less is more: exploring outcomes of Twitter usage in the large-lecture hall. *Learning, Media and Technology*, *36*(3), 215–233.

Erickson, I. (2008). The translucence of Twitter. In *Ethnographic Praxis in Industry Conference Proceedings* (Vol. 2008, pp. 64–78). Wiley Online Library. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/j.1559-8918.2008.tb00095.x/abstract

Freeman, L. (2009). *Methods of Social Network Visualization*. Berlin: Springer.

Freeman, L. C. (2000). Visualizing social networks. *Journal of Social Structure*, *1*(1), 4.

Gann, D. M., & Salter, A. J. (2000). Innovation in project-based, service-enhanced firms: the construction of complex products and systems. *Research Policy*, *29*(7), 955–972.

García-Peñalvo, F. J., Colomo-Palacios, R., & Lytras, M. D. (2012). Informal learning in work environments: training with the Social Web in the workplace. *Behaviour & Information Technology*, *31*(8), 753–755.

García-Peñalvo, F. J., Cruz-Benito, J., Borrás-Gené, O., & Blanco, Á. F. (2015). Evolution of the Conversation and Knowledge Acquisition in Social Networks related to a MOOC Course. In *Learning and Collaboration Technologies* (pp. 470–481). Springer. Retrieved from http://link.springer.com/chapter/10.1007/978-3-319-20609-7_44

Giuliani, E., & Bell, M. (2008). Industrial clusters and the evolution of their knowledge networks: revisiting a Chilean case. Retrieved from https://smartech.gatech.edu/handle/1853/35134

Gómez-Aguilar, D.-A., García-Peñalvo, F.-J., & Therón, R. (2014). ANALíTICA VISUAL EN e-learning. *El Profesional de La Información*, *23*(3), 236–245.

Gómez-Aguilar, D. A., Therón, R., & García Peñalvo, F. J. (2013). Reveal the relationships among student's participation and its outcomes on eLearning environments: Case study. In *Advanced Learning Technologies, 2013. ICALT 2013. 13th IEEE International Conference on* (pp. 15–18).

Gomez-Aguilar, D., Conde-Gonzalez, M., Theron, R., & Garcia-Peñalvo, F. (2011). Supporting moodle-based lesson through visual analysis. In *Human-Computer Interaction–INTERACT 2011* (pp. 604–607). Springer. Retrieved from http://link.springer.com/chapter/10.1007/978-3-642-23768-3_93

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, 1360–1380.

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic Management Journal*, *17*, 109–122.

Gruzd, A., Wellman, B., & Takhteyev, Y. (2011). Imagining Twitter as an imagined community. *American Behavioral Scientist*, *55*(10), 1294–1318.

Hansen, D. L., Rotman, D., Bonsignore, E., Milic-Frayling, N., Rodrigues, E. M., Smith, M., … Capone, T. (2009). Do you know the way to SNA?: A process model for analyzing and visualizing social media data. *U. of Maryland Tech Report: HCIL-2009-17*. Retrieved from http://www.smrfoundation.org/wp-content/uploads/2010/05/2009-UMD-TechReport-Do-you-know-the-way-to-SNA.pdf

Hansen, D., Shneiderman, B., & Smith, M. A. (2010). *Analyzing social media networks with NodeXL: Insights from a connected world*. Morgan Kaufmann. Retrieved from http://www.google.com/books?hl=fi&lr=&id=rbxPm93PRY8C&oi=fnd&pg=PP2&dq=Analyzing+Social+Media+Networks+with+NodeXL:+Insights+from+a+Connected+World,+&ots=MxfD59-rH6&sig=tVXZENpTlmFwBDWcM9BjJ5T4nZo

Heer, J., & Shneiderman, B. (2012). Interactive dynamics for visual analysis. *Queue*, *10*(2), 30.

Hey, A. J., Tansley, S., & Tolle, K. M. (2009). The fourth paradigm: data-intensive scientific discovery. Retrieved from http://iw.fh-potsdam.de/fileadmin/FB5/Dokumente/forschung/tagungen/i-science/TonyHey_-__eScience_Potsdam__Mar2010____complete_.pdf

Hobday, M. (2000). The project-based organisation: an ideal form for managing complex products and systems? *Research Policy*, *29*(7), 871–893.

Huberman, B. A., Romero, D. M., & Wu, F. (2008). Social networks that matter: Twitter under the microscope. *arXiv Preprint arXiv:0812.1045*. Retrieved from http://arxiv.org/abs/0812.1045

Huhtamäki, J., Nykänen, O., & Salonen, J. (2009). Catalysing the development of a conference workspace. In *Online Communities and Social Computing* (pp. 43–52). Springer. Retrieved from http://link.springer.com/chapter/10.1007/978-3-642-02774-1_5

Huhtamäki, J., Russell, M. G., Rubens, N., & Still, K. (2015). Ostinato: The exploration-automation cycle of user-centric, process-automated data-driven visual network analytics. In E. Bertino, S. Matei, & M. G. Russell (Eds.), *Roles, Trust, and Reputation in Social Media Knowledge Markets*. Springer.

Intons-Peterson, M. J., & Newsome III, G. L. (1992). External memory aids: Effects and effectiveness. In *Memory Improvement* (pp. 101–121). Springer. Retrieved from http://link.springer.com/chapter/10.1007/978-1-4612-2760-1_7

Java, A., Song, X., Finin, T., & Tseng, B. (2007). Why we twitter: understanding microblogging usage and communities. In *Proceedings of the 9th WebKDD and 1st SNA-KDD 2007 workshop on Web mining and social network analysis* (pp. 56–65). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=1348556

Junco, R., Elavsky, C. M., & Heiberger, G. (2013). Putting twitter to the test: Assessing outcomes for student collaboration, engagement and success. *British Journal of Educational Technology*, *44*(2), 273–287.

Junco, R., Heiberger, G., & Loken, E. (2011). The effect of Twitter on college student engagement and grades. *Journal of Computer Assisted Learning*, *27*(2), 119–132.

Jussila, J., Huhtamäki, J., Kärkkäinen, H., & Still, K. (2013). Information visualization of Twitter data for co-organizing conferences. In *Proceedings of the 17th International Academic MindTrek Conference: Making Sense of Converging Media*. Tampere.

Jussila, J., J Huhtamäki, K Henttonen, H Kärkkäinen, & K Still. (2014). Visual Network Analysis of Twitter Data for Co-organizing Conferences: Case CMAD 2013. In *Proceedings of the 47th Annual Hawaii International Conference on System Sciences* (Vol. January 6–9).

Jussila, J. J., Kärkkäinen, H., & Leino, M. (2012). Learning from and with Customers with Social Media: A Model for Social Customer Learning. *International Journal of Management, Knowledge and Learning*, *1*(1), 5–25.

Kassens-Noor, E. (2012). Twitter as a teaching practice to enhance active and informal learning in higher education: The case of sustainable tweets. *Active Learning in Higher Education*, *13*(1), 9–21.

Konno, N., Nonaka, I., & Ogilvy, J. (2014). Scenario planning: The basics. *World Futures*, *70*(1), 28–43.

Koskinen, K. U., & Aramo-Immonen, H. (2008). Remembering with the help of personal notes in a project work context. *International Journal of Managing Projects in Business*, *1*(2), 193–205.

Lave, J., & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation*. Cambridge university press. Retrieved from http://www.google.com/books?hl=fi&lr=&id=CAVIOrW3vYAC&oi=fnd&pg=PA11&dq=situated+learning+legitimate+peripheral+participation&ots=OBkBqtZHBi&sig=-66nkDbHt-t2M5f90QqOihkr7wk

Leskovec, J., Backstrom, L., & Kleinberg, J. (2009). Meme-tracking and the dynamics of the news cycle. In *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 497–506). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=1557077

Liu, Y.-Y., Slotine, J.-J., & Barabási, A.-L. (2011). Controllability of complex networks. *Nature*, *473*(7346), 167–173.

Loureiro-Koechlin, C., & Butcher, T. (2013). The emergence of converging communities via Twitter. *The Journal of Community Informatics*, *9*(3). Retrieved from http://ci-journal.taniasunde.com/index.php/ciej/article/view/705

Meacham, J. A., & Leiman, B. (1982). Remembering to perform future actions. *Memory Observed: Remembering in Natural Contexts*, 327–336.

Merigó, J. M., Rocha, C., & Garcia-Agreda, S. (2013). Entrepreneurial intervention in electronic markets: the influence of customer participation. *International Entrepreneurship and Management Journal*, *9*(4), 521–529.

Moreno, J. L. (1953). Who shall survive? Foundations of sociometry, group psychotherapy and socio-drama . Retrieved from http://psycnet.apa.org/psycinfo/1954-04178-000

Nonaka, I., & Takeuchi, H. (1995). *The Knowledge-Creating Company: How Japanese Companies Create the Dynamics of Innovation: How Japanese Companies Create the Dynamics of Innovation*. New York: Oxford University Press. Retrieved from http://www.google.com/books?hl=fi&lr=&id=B-qxrPaU1-

MC&oi=fnd&pg=PA3&dq=nonaka+knowledge+creating+company&ots=XgZMnwsihY&sig=uZcw6er74CSraZHdULf_2R8-fKw

North, C. (2006). Toward measuring visualization insight. *Computer Graphics and Applications, IEEE*, *26*(3), 6–9.

Patil, D. J. (2012). *Data Jujitsu: The Art of Turning Data into Product*. O'Reilly Media, Inc.

Popper, M., & Lipshitz, R. (1998). Organizational learning mechanisms a structural and cultural approach to organizational learning. *The Journal of Applied Behavioral Science*, *34*(2), 161–179.

Prencipe, A., & Tell, F. (2001). Inter-project learning: processes and outcomes of knowledge codification in project-based firms. *Research Policy*, *30*(9), 1373–1394.

Raivola, R., & Ropo, E. (1991). Jatkuva Koulutus ja Elinikäinen Oppiminen (Continuous Training and Life-long Learning). *Tampere, TAY Julkaisusarja A: Tutkimusraportti*, *9*.

Ritala, P., & Hallikas, J. (2011). Network position of a firm and the tendency to collaborate with competitors–a structural embeddedness perspective. *International Journal of Strategic Business Alliances*, *2*(4), 307–328.

Ritala, P., & Huizingh, E. (2014). Business and network models for innovation: strategic logic and the role of network position. *International Journal of Technology Management*, *66*(2), 109–119.

Ropes, D. C. (2010). Organizing professional communities of practice. Retrieved from http://dare.uva.nl/document/177064

Russell, M. G., Huhtamaki, J., Still, K., Rubens, N., & Basole, R. C. (2015). Relational Capital for Shared Vision in Innovation Ecosystems. *Triple Helix: A Journal of University-Industry-Government Innovation and Entrepreneurship (THJI)*.

Russell, M. G., Still, K., Huhtamäki, J., Yu, C., & Rubens, N. (2011). Transforming innovation ecosystems through shared vision and network orchestration. In *Triple Helix IX International Conference. Stanford, CA, USA*.

Sarala, U. (1993). *Madaltuvat organisaatiot, itseohjautuvat pienryhmät: kahvikerhosta oppivaan organisaatioon*. Suomen laatuyhdistys, laatupiirijaos.

Schreiber, M., & Engelmann, T. (2010). Knowledge and information awareness for initiating transactive memory system processes of computer-supported collaborating ad hoc groups. *Computers in Human Behavior*, *26*(6), 1701–1709.

Schultze, U., & Stabell, C. (2004). Knowing what you don't know? Discourses and contradictions in knowledge management research. *Journal of Management Studies*, *41*(4), 549–573.

Shakarian, P., Eyre, S., & Paulo, D. (2013). A scalable heuristic for viral marketing under the tipping model. *Social Network Analysis and Mining*, *3*(4), 1225–1248.

Silius, K., Tervakari, A.-M., & Kailanto, M. (2013). Visualizations of user data in a social media enhanced web-based environment in higher education. In *Global Engineering Education Conference (EDUCON), 2013 IEEE* (pp. 893–899). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6530212

Stephansen, H. C., & Couldry, N. (2014). Understanding micro-processes of community building and mutual learning on Twitter: a "small data"approach. *Information, Communication & Society*, (ahead-of-print), 1–16.

Still, K., Huhtamäki, J., Russell, M. G., & Rubens, N. (2014). Insights for orchestrating innovation ecosystems: the case of EIT ICT Labs and data-driven network visualisations. *International Journal of Technology Management*, *66*(2), 243–265.

Teaching Research Institute. (2011). Using External Aids to Compensate for Memory and Organizational Problems Post-TBI. Retrieved March 15, 2015, from http://www.brainline.org/content/2011/04/using-external-aids-to-compensate-for-memory-and-organizational-problems-post-tbi.html

Telea, A. C. (2014). *Data visualization: principles and practice*. CRC Press. Retrieved from http://www.google.com/books?hl=fi&lr=&id=2WoLBAAAQBAJ&oi=fnd&pg=PP1&dq=.+Data+visualization:+principles+and+practice&ots=Zny6CjUNa-&sig=P-XIIAiUFHil8XRbdih6ljhcBSw

Tervakari, A., Silius, K., Tebest, T., Marttila, J., Kailanto, M., & Huhtamaki, J. (2012). Peer learning in social media enhanced learning environment. In *Global Engineering Education Conference (EDUCON), 2012 IEEE* (pp. 1–9). IEEE. Retrieved from http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6201109

Thomas, J. J., & Cook, K. A. (2006). A visual analytics agenda. *Computer Graphics and Applications, IEEE*, *26*(1), 10–13.

Ware, C. (2004). *Information Visualization: Perception for Design*. San Francisco: Elsevier.

Wegner, D. M. (1987). Transactive memory: A contemporary analysis of the group mind. In *Theories of group behavior* (pp. 185–208). Springer. Retrieved from http://link.springer.com/chapter/10.1007/978-1-4612-4634-3_9

Wegner, D. M. (1995). A computer network model of human transactive memory. *Social Cognition*, *13*(3), 319–339.

Wenger, E. (1998). *Communities of practice: Learning, meaning, and identity*. Cambridge university press. Retrieved from http://www.google.com/books?hl=fi&lr=&id=heBZpgYUKdAC&oi=fnd&pg=PR11&dq=communities+of+practice+learning+meaning+and+identity&ots=kekdXr9y4l&sig=88nqnWC-lksnMoDvfELfSg7kFLg

Wenger, E., McDermott, R. A., & Snyder, W. (2002). *Cultivating communities of practice: A guide to managing knowledge*. Harvard Business Press. Retrieved from http://www.google.com/books?hl=fi&lr=&id=m1xZuNq9RygC&oi=fnd&pg=PR9&dq=Cultivating+communities+of+practice&ots=ZU17dL6fd-&sig=EmRtAsYUGp7ssqwHUh3uthpiWLo

Weng, L., Menczer, F., & Ahn, Y.-Y. (2013). Virality prediction and community structure in social networks. *Scientific Reports*, *3*. Retrieved from http://www.nature.com/srep/2013/130828/srep02522/full/srep02522.html?WT.ec_id=SREP-639-20130902

Zappavigna, M. (2012). *Discourse of Twitter and social media: How we use language to create affiliation on the web*. Bloomsbury Publishing.