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Mining E-mail to Leverage Knowledge Networks in Organizations

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Abstract: There is nothing new about the notion that in today's knowledge driven economy, knowledge is the key strategic asset for competitive advantage in an organization. Also, we have learned that knowledge is residing in the organization's informal network. Hence, to leverage business performance from a knowledge management perspective, focus should be on the informal network. A means to analyze and develop the informal network is by applying Social Network Analysis (SNA). By capturing network data in an organization, bottlenecks in knowledge processes can be identified and managed. But where network data can easily be captured by means of a survey in small organizations, in larger organizations this process is too complex and time-intensive. Mining e-mail data is more and more regarded as a suitable alternative as it automates the data capturing process and enables longitudinal research possibilities. An increasing amount of tools for mining e-mail data into social networks is available, but the question remains to what extent these tools are also capable of conducting knowledge network analysis: the analysis of networks from a knowledge perspective. It is argued that in order to perform knowledge network analysis, a tool is required that is capable of analyzing both the header data and the body data of e-mail messages. In this paper two e-mail mining tools are elaborated. One focuses on the analysis of e-mail header data and the other focuses on the analysis of e-mail body data. Both tools are embedded in their theoretical background and compared to other e-mail mining tools that address e-mail header data or e-mail body data. The aim of this paper is two-fold. The paper primarily aims at providing a detailed discussion of both tools. Continuing, from the in-depth review, the integration of both tools is proposed, concluding towards a single new tool that is capable of analyzing both e-mail header and body data. It is argued how this new tool nurtures the application of knowledge network analysis.

Keywords: e-mail mining, knowledge management, knowledge networks, social network analysis

1. Introduction

Informal networks are based on social relations between people that cross traditional hierarchical relations in organizations (Krackhardt & Hanson, 1997). These informal networks connect people horizontally rather than vertically and are used for many different purposes, such as finding expertise, problem solving, seeking advice or collaboration. It is often through these informal networks that problems are solved that are encountered when strictly following the formal work descriptions of an organization (Brown & Duguid, 1991). Or as Cross & Parker (2004) state, the informal networks explain “how work really gets done in organizations”. Informal networks also play an important role from a knowledge management perspective. In this context, they are also referred to as knowledge networks (Wenger, McDermott, & Snyder, 2002)(Back, Krogh, Seufert, & Enkel, 2005)(Helms & Buysrogge, 2006) Within knowledge networks, more specific networks could be identified if one focuses on a particular activity such as learning (learning networks) or seeking advice (advice networks) (Borgatti & Cross, 2003) (Skerlavaj, Dimovski, Mrvar, & Pahor, 2008). One particular sub-discipline of knowledge management focuses on studying knowledge networks from a structural point of view, using Social Network Analysis (SNA) techniques. By studying the patterns of these networks, these researchers try to identify malfunctions of knowledge networks or common patterns in successful networks (Back et al., 2005)(Helms, 2007)(Liebowitz, 2005)(Mueller-Prothmann & Finke, 2004)(Marouf, 2007)(Cheuck, 2006). Applying network analysis implies that network data needs to be collected. Traditionally, this is done through surveys or questionnaires (Hanneman, 2007). A disadvantage of surveys is that, especially for large surveys, it takes considerable time from the respondent to fill out the survey and also that high response rates are required to do qualitative analysis in case studies (Helms, 2007)(Teigland, 2002). Consequently, there is hardly any longitudinal analysis of knowledge networks as it requires that a survey is sent out several times during a certain period. But as knowledge sharing or knowledge creation is based on communication and social interaction, it might be worthwhile to consider the use of e-mail data as sources for collecting network data. In previous research, we already demonstrated for one case in a knowledge intensive organization that there is a significant correlation between the e-mail network and the knowledge network of that organization (van Reijssen & Helms, 2008). As this seems a promising field that can bring the analysis of knowledge networks a step further, we developed a tool that is capable of analyzing and refining e-mail data in order to construct social networks. The tool focuses on e-mail header data (i.e. to, from, subject and time fields). The pitfall of this approach is that, even while our earlier study provided strong argumentation that our approach uncovers actual knowledge networks from e-mail data, there is no 100% certainty that the uncovered network is in fact a knowledge network comprising of knowledge transfer. Moreover, our approach does not provide any understanding in what knowledge topics are actually distributed over the network. This deficiency calls for a complementary approach in which the e-mail body data (i.e. the body of the message) is also regarded. A tool that combines both e-mail header and body data can construct a network map from the e-mail header data and plot knowledge topics on the network map derived from the e-mail body data.

The remainder of this paper is structured as follows. In section 2, our initial e-mail header data analysis tool is discussed in detail. Moreover, it is compared with similar tools on a variety of characteristics. In section 3, a complementary tool is discussed that focuses on the analysis of e-mail body data. Section 4 proposes the integration of both tools into a single new tool and discusses how this new tool may be appropriate for conducting knowledge network analysis. Finally, section 6 concludes our paper and scopes on future research opportunities.

2. ESNE: E-mail Social Network Analysis

2.1 Introduction to ESNE

E-mail Social Network Extraction (ESNE) is a tool that is specialized in mining header data from e-mail messages. ESNE uses raw Microsoft Exchange data as input to identify nodes and edges to construct a social network (sociogram) based on e-mail messages exchanged in a controlled environment (e.g. an organization). ESNE uses the sender and receiver information from e-mail headers to identify which nodes are present and which edges exist between the identified nodes. In identifying senders and

receivers as edges, ESNE is capable of identifying alternative e-mail addresses that represent the same edge, e.g. an employee in an organization, by automatically scanning names in e-mail addresses or by manually comparing e-mail addresses. Moreover, ESNE contains strong filtering options that are relevant to create specific network slices for specific research ends. ESNE can filter e-mail for a specific domain, e.g. leaving only e-mail messages sent and received between employees of a focal organization or department. Also, it filters out mass mail messages (e.g. an e-mail sent to over 30 employees) as it is argued that this form of e-mailing does not represent individual knowledge exchange. Automatically created messages can also be filtered out (e.g. an out of office reply). The combination of these characteristics enables ESNE to create specific social network slices from raw e-mail data, enabling analysts to study specific network scenarios.

2.2 Deriving networks from header data

The header of an e-mail message contains valuable information that can be used to construct a social network of people, sending e-mail in a specific domain (e.g. an organization) and timeframe (e.g. a month). The header data of e-mail consists of 3 parts that are relevant for constructing a social network: sender/receiver information, the subject and the timestamp. The sender and receiver information can be used to track who is sending e-mail to whom. Hence, the sender and receiver information is by itself already adequate information to construct a social network from, consisting of nodes (senders and receivers) and edges (the link between nodes that exists as a result of an e-mail message sent between both nodes). The subject of an e-mail message can be additionally applied in the construction of a social network. It adds contextual information to the edges of the social network by e.g. identifying whether an edge is reciprocated (symmetric) due to a reply on a message or due to several distinct messages sent from and to both nodes. The timestamp of an e-mail message can be applied for filtering purposes, enabling the construction of a social network from e-mail from e.g. one month. Also, a filter can be in place that counts edges only if a message has been replied to within a specific timeframe.

2.3 Tools for mining header data

In order to position the ESNE tool in its domain among other tools, a literature study has been conducted to identify existing tools that mine e-mail header data to construct a social network. Moreover, for each identified tool, we analyzed to what extent the tool uses the 3 parts of header data, thus providing characteristics for each tool. In our study, 5 tools have been identified: Themail (Viegas, Golder & Donath, 2006), Condor (Gloor, 2004), Metasight (Edwards, 2005), Flint (Mika, 2005) and Commetrix (Trier, 2006). Also, we analyzed the tools for their capability of handling e-mail aliases and handling filters. Handling e-mail aliases concerns the identification and translation of alternative e-mail addresses that belong to one sender (one node). If a tool can handle aliases, it can find e-mail addresses and corresponding messages, based on e.g. the name of a sender or receiver and combine those messages with the messages that originate from the initial e-mail address. Handling filters concerns filtering out senders and receivers when constructing a social network. By applying filters, specific social networks can be constructed, e.g. a network only depicting strong ties by filtering out edges that are based on only a few messages exchanged between sender and receiver. In table 1 below, an overview is provided of the tools of our study, indicating what specific header data is used by each tool. Additionally, ESNE is included to compare the results to.

Tool	Sender/Receiver	Subject	Timestamp	Aliases	Filters
Themail	yes	no	yes	yes	no
Condor	yes	no	yes	yes	no
Metasight	yes	yes	yes	no	no
Flink	yes	yes	yes	no	no
Commetrix	yes	no	yes	no	yes
ESNE	yes	no	yes	yes	yes

Table 1: Overview of tools for creating social networks from e-mail header data

2.4 Analysis

As can be derived from table 1, all tools apply the sender/receiver part of the header data in constructing a social network. This option is, however, expected as the sender/receiver information is a prerequisite for constructing an overview of nodes and edges. Not all tools apply the subject and timestamp parts in order to construct a more sophisticated network. What is more striking is the fact that only few tools support the aliases functionality and that most tools do not provide filtering options. Especially the filtering option is regarded as an essential characteristic of any e-mail mining tool as it enables researchers to refine the raw e-mail data for specific research questions. In fact, in many research initiatives where e-mail was mined to construct a social network, researchers applied filters to refine their e-mail data manually (Adamic & Adar, 2005; Arenas et al., 2004; Culotta, Bekkerman & Mccallum, 2004; Bird et al., 2006; Balog & De Rijke, 2006). While ESNE is a tool that cannot visualize a social network from e-mail data, it specifically focuses on refining e-mail data for specific research ends by providing many filtering options. ESNE is the only tool that supports both e-mail aliases and filters. Figure 1 displays a screenshot of the ESNE interface.

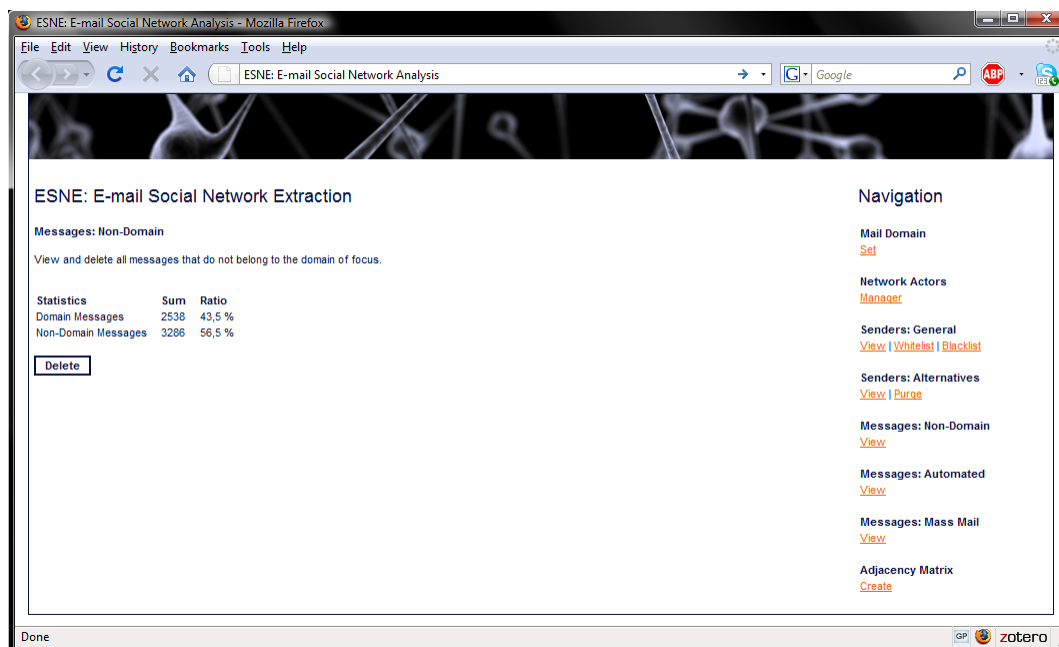


Figure 1: Application of ESNE: E-mail Social Network Extraction

2.5 Application of ESNE in practice

In 2008, ESNE was successfully applied in a Dutch IT services organization. The organization of focus was going through a large organizational change, where the current management team was replaced by a new management team. The board of directors required a means to keep track of the change process in terms of how knowledge flows from and to the management team in the old and the new scenario. ESNE was applied to construct three social networks from e-mail data of the full organization: one slice before the transition, one slice during the transition and 1 slice after the transition. Each slice concerned a timeframe of one month. Before the analysis of the data, ESNE filters were applied to fine the data: only domain messages were considered, only edges of more than 20 messages per month were considered, mass mail messages were ignored and automatically generated messages (e.g. out of office reply) were ignored. The refined data, once imported in Cyram's Netminer 2.60a, resulted in three network slices that exactly depicted how the new management team emerged as a key knowledge player in the center of the organizational network. ESNE helped the board of directors in understanding and managing the transition of the management team. Figure 4 displays the end-state slice, displaying the new management team in the largest dotted border.

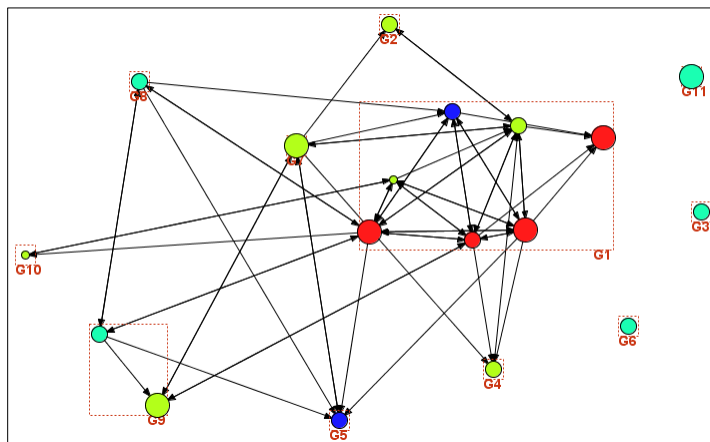


Figure 4: end-state slice from the Dutch IT-services organization analysis

2.6 Discussion

Concluding from this section, ESNE is argued to be a strong tool for analyzing and refining e-mail body data in order to construct social networks. However, regarded from the viewpoint of providing a tool that is capable of conducting knowledge network analysis, ESNE is lacking functionality. Our tool does not incorporate e-mail body data in its analysis. The next section discusses a complementary tool that is capable of analyzing e-mail body data.

3. EKE: E-mail Knowledge Extraction

3.1 Introduction to EKE

Opposed to ESNE, E-mail Knowledge Extraction (EKE) is a tool that is specialized in mining body data from e-mail messages. EKE consists of a front-end and a back-end. The front-end represents a plug-in that can be installed in outlook. If senders within a specific domain (e.g. an organization) send e-mail messages to their receivers, EKE tracks specific words used in the body of an e-mail message and asks the sender to what extent he/she is knowledgeable about that word. This information is stored in EKE's back-end, hence creating a database containing an overview of senders (e.g. employees) and their knowledge on specific topics. The back-end is searchable for e.g. other employees in order to track

knowledge ownership and e.g. to identify whom to approach when an employee searches for knowledge on a specific topic.

3.2 Deriving knowledge from body data

Email has several characteristics which makes it suitable for inclusion in a semi-automated/automated application to finding knowledge. It supports key knowledge processes such as knowledge creation and sharing. Moreover, it creates an electronic record of these knowledge processes, making it possible to track and link daily workflows to the people involved (Lichtenstein, 2004). However, extracting key phrases that describe the individual's expertise from an email body poses an immense challenge. Emails are freestyle text, not always syntactically well formed, domain independent, of variable length, and on multiple topics (Tzoukermann et al., 2001).

3.3 Tools for mining body data

There have been numerous attempts to create tools which utilize email as their source of information including *Tacit's ActiveNet* (Tacit Software, 2007), AskMe Enterprise (AskMe) and Corporate Smarts' Intelligent Directory (Corporate Smarts). Expert locator systems have been implemented in a variety of organizational domains (Maybury, 2002). Successful deployment of such systems is dependent on many factors including: user involvement, the establishment of clear objective(s)/purpose(s), measured usage and benefit, ease of use, incremental deployment, appropriate privacy, incentives for use, and effective training (Maybury, 2002).

Figure 2 shows how such systems can be used to analyze emails to identify individuals or groups that have specific expertise. When an email is sent (step 1 in Figure 2), key phrases are extracted (step 2 in Figure 2). The extracted key phrases are then sent back to the user (step 3 in Figure 2) and placed into an expertise profile that the user can edit (step 4 in Figure 2). The expertise profile contains information about 'who knows what' within the organization. This information is then distilled into a searchable database (step 5 in Figure 2) which users can query to find relevant people.

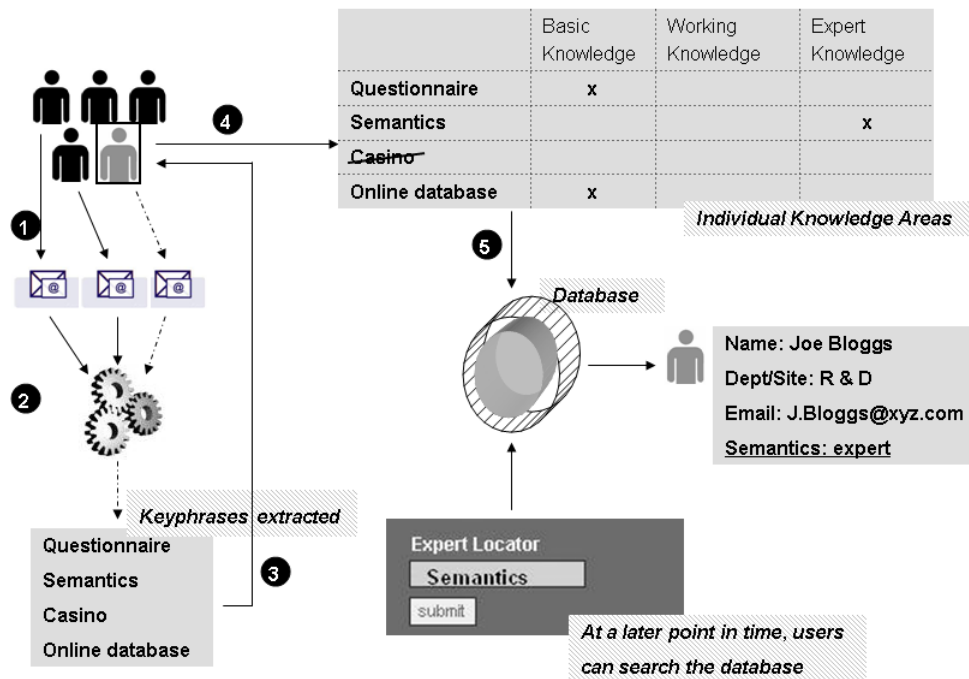


Figure 2: Schematic representation of e-mail content analysis

3.4 Analysis

Not all systems perform steps 3 and 4 and in this particular case. These steps are specific to the system some of the authors have developed that is called Email Knowledge Extraction (EKE). Users are provided with an interface to rank their knowledge in the extracted keyphrases. With regards to similar extraction systems and how they work, most of the system information is only available in the form of white papers serving as a marketing tool to promote an organizations product and point of view which potentially could be biased.

An important argument why EKE outperforms other tools that extract e-mail body data is that EKE works in a prescriptive way. Compared to keyword searching, EKE does not only provide a means to search information in a database (step 5 in Figure 2), which may be labelled as descriptive, but in fact captures all possible knowledge areas. With EKE, a list is generated from knowledge topics that are derived from e-mail messages. This is different from a keyword searching mechanism that is only capable of searching through the entire e-mail database for specific keywords.

Moreover, EKE adds important metadata to identified knowledge topics as it captures which person is knowledgeable of the topic and what the expertise level of this person is regarding the knowledge topic. In the field of knowledge management, these are relevant variables.

A final strong characteristic of EKE is that it secures privacy in a most comprehensive way. Senders of e-mail messages are themselves asked what topics they are knowledgeable of and may choose to discard topics that are not relevant or private of nature. Hence, only the topics that the sender indicates are stored as searchable knowledge topics. Figure 3 displays a screenshot of the EKE interface.

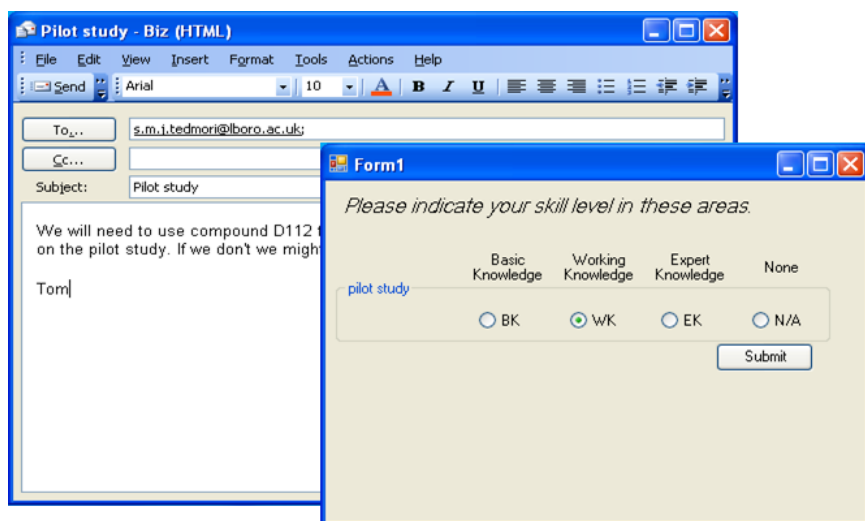


Figure 3: Application of EKE: E-mail Knowledge Extraction

3.5 Application of EKE in practice

A study was conducted at the Department of Information Science at Loughborough University with the aim of obtaining feedback from potential end users on functionality, robustness, clarity, and ease of use in a working environment.

After a six-week period of using EKE had past, the participants were asked to fill in a post-study questionnaire tackling areas related to EKE's performance, usability, and handling of socio-ethical challenges. As part of this questionnaire, participants were provided with a list of their key proficiencies, identified from their e-mail communications by EKE. Participants were asked to judge how well the key

proficiencies identified reflect their areas of knowledge. Results from this study provided valuable feedback on the end-users' perceptions of the EKE tool and to the enablers and the barriers to its adoption.

From the comments made, the concept of EKE was regarded as a good, useful, and interesting idea. It was suggested that the information captured by EKE could be used for personal ratings for the purpose of personal development. The key phrases extracted would highlight where an individual had expertise and where an individual might benefit from training as EKE could highlight a gap in their skill set. It was felt that EKE's ability to integrate with existing technologies (i.e. Outlook) would encourage its adoption and use.

When given the choice, 90% of participants said that they preferred to extract key phrases from email using EKE rather than manually. The majority of participants who favoured EKE attributed this primarily to the speed of the system and its ease of use. Another reason mentioned was the tool's good coverage of main email subject categories.

3.6 Discussion

Given the e-mail body data analysis capabilities of EKE and the e-mail header data analysis capabilities of ESNE, both tools are regarded complementary to each other. The Integration of both tools may result in a single new tool that combines both analysis capabilities and hence enables conducting knowledge network analysis. The next section proposes the integration of ESNE and EKE into a single new tool.

4. Integration of ESNE and EKE

While ESNE is capable of creating a social network from e-mail data, it cannot identify to what extent the exchanged messages comprise of knowledge transfer. Consequently, while EKE is capable of identifying knowledge areas among a group of senders and receivers, it cannot depict these knowledge areas within a social network. The integration of both tools results in a single new tool that is capable of analyzing and representing who-knows-who and who-knows-what. Because the new tool could identify knowledge transfer within a constructed social network, the tool would be capable of constructing knowledge networks.

4.1 Application of ESNE and EKE combined

By combining the ability of ESNE to construct a social network from header data and the ability of EKE to identify knowledge topics, the integrated tool would be capable of mapping (emerging) knowledge areas on the plotted social network of e.g. an organization. This is an interesting feature as the tool can be used to identify informal knowledge communities within an organization that were not recognized before. Furthermore, the integrated tool enables longitudinal analysis where it is possible to study how the knowledge communities emerge and what dynamics exist between the communities. Instead of on an organizational level, it is also possible to study individual knowledge communities. The tool provides data on the expertise level of each individual in the community and on the frequency of communication with other community members. Additionally, a longitudinal analysis can be conducted to study how a community evolves and how the role of the different members changes over time. In order to integrate both ESNE and EKE, a common back-end is required to map the senders of e-mail messages (from ESNE) on the owners of specific knowledge topics (as stored in EKE).

5. Conclusions

5.1 Conclusion

In this paper, two different types of e-mail mining tools were discussed in detail. One tool can plot social networks from e-mail header data and the other tool can extract expertise of employees from e-mail body data. Moreover, the integration of both tools was discussed, concluding towards a tool that is capable of creating knowledge networks from mining e-mail messages in a controlled environment (e.g. an organization). The integration of both tools enables constructing knowledge networks from e-mail data by identifying knowledge transfer relation between people as well as where particular knowledge resides in a social network. The unique feature of the integrated tool of constructing knowledge networks enables both researchers and practitioners to apply knowledge network analysis in organizations while using single source e-mail traffic as a data collection source. Knowledge network analysis is becoming increasingly popular among both scholars and practitioners in analyzing and managing organizational knowledge from a network perspective. Current means to conduct knowledge network analysis are mainly restricted to surveying. As surveying knows several limitations (i.e. difficult to perform in large organizations, difficult to perform longitudinal analysis), finding alternative means to collect network data is a relevant research topic. This paper intends to provide new means in conducting knowledge network analysis, by proposing a tool that can mine e-mail traffic to uncover both the existence of a knowledge transfer relation, the knowledge that is being transferred, and the expertise of the people in the network. Using the combined tools, data collection becomes easier and provides better opportunities for longitudinal analysis of knowledge networks.

5.2 Limitations

The actual integration of both individual tools is not yet a fact. This paper is moreover a proposal and argues for the strengths and areas of application of the combination of both tools. Therefore, this paper cannot conclude on the usability of the tool and on the applicability of the tool for conducting knowledge network analysis, but the outlook is promising.

5.3 Future work

The next step in our research initiative is to integrate ESNE and EKE into a single application. Also, the newly developed application has to be applied in a case study environment to test the application itself and to test whether the application is capable of conducting knowledge network analysis. Both steps are required before we can conclude on the added value of the integrated tool in the field of knowledge network analysis. Future work will elaborate on the integration process and application of the integrated tool. Another issue that requires attention is the privacy of the employees in an organization. Although we have experience in applying both tools separately, the combination of the tools might be regarded as intrusive from a privacy perspective. Without paying close attention to the privacy issue, organizations may not be willing to apply the tool or to participate in research that applies the tool.

Acknowledgements

The authors would sincerely like to thank the Comprehend Platform for providing the resources to develop ESNE. Also, the authors would like to thank the Loughborough University for supporting the development of EKE.

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