Redesigning Communities of Practice using Knowledge Network Analysis

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Snapshot (Quick Learning)

The performance of many companies in today's knowledge economy relies on informal networks. Such networks promote the lateral sharing of knowledge between employees, which results in sharing best practices and innovations. Informal networks have received a lot of attention in literature and they are referred to as *communities of practice*. Several authors agree that communities make employees more effective in dealing with knowledge and contribute to the performance of the organization (Epple, Argote & Murphy, 1996; Cross & Parker, 2004). Therefore, also the effective and efficient implementation of communities of practice received much attention.

There are several handbooks available on how to create and develop communities, such as the approach described by Wenger, McDermott & Snyder (2000) and the Seduce, Engage and Sustain (SES) model from Dignum & Van Eeden (2003). Typically, these approaches have a process focus because they describe the phases and activities required to implement a community of practice. The Knowledge Network Analysis technique, which is described in this chapter, is complementary to such approaches because it makes it possible to make a *snapshot* of a community of practice. A snapshot is a representation of a community of practice from a network perspective. It views a community as a network of connected people, where the nodes in the network represent the people and the lines between the nodes represent knowledge exchanges between the people. Using a network perspective it is possible to study the structural properties of a network. These properties tell something about the soundness of the community and whether the structure enables or disables the community to achieve its goals. In Knowledge Network Analysis these structural properties are used to detect knowledge sharing bottlenecks in communities of practice. Furthermore, they form the basis for (re)designing a community of practice in order to improve its performance.

The Knowledge Network Analysis technique is intended for practitioners responsible for the development and support of communities of practice. It is typically applied to the members of a single community. There is not really a maximum with respect to the number of people in a community. Although, in later chapters it becomes clear that for large communities (>50-75 people) the data collection becomes rather labour intensive. If the number of people is limited to 50-75 people the Knowledge Network Analysis can be completed in a 3-4 week period.

Keywords: Knowledge Networks, Knowledge Network Analysis, Social Network Analysis, Communities of Practice

Context (Where & What)

Push networks: Developing professional skills

Communities of practice are: "*groups of people informally bound together by shared expertise and passion for a joint enterprise"* (Wenger & Snyder, 2000). Simply stated, it is an informal network of people that share knowledge in a particular domain or knowledge area: "*a coherent clusters of insights, experiences, theories, and heuristics*" (Schreiber, Akkermans et al., 2002). An example of a knowledge area in an engineering firm is for instance knowledge concerning the design of railroads or jetties. The people that exchange this kind of knowledge with each other form the community of practice. Knowledge in such a community is shared through a variety of channels such as meetings, personal discussions, teleconferences, e-mail, discussion groups etc. Moreover, there contacts do not follow an explicit agenda and there are no formal deliverables defined that should be completed before a certain deadline.

In practice several types of communities of practice can be distinguished by looking at how they add value to a company (Wenger & Snyder, 2000). Knowledge Network Analysis focuses on one type of community. This type of community is called a *push network* (Helms & Buysrogge, 2006) and aims to develop the professional skills of its members. The professional skills of an employee are also referred to as "*deep smarts*" (Leonard & Swap, 2005). Deep smarts enable a person to quickly analyze a situation and come up with a smart solution. An example is a computer engineer that is able to quickly identify a hardware problem without having to go systematically through all the possible failure options. In practice, organizations often describe such deep smarts in terms of expertise levels of their employees. An example of commonly used expertise levels involves: trainee, novice, and expert.

When the job performance of an employee with deep smarts is compared to an employee without deep smarts, the first will come up with a better solution, within a shorter time (Leonard et al., 2005). Therefore, it is in the interest of the organization that employees with these deep smarts share their knowledge with their colleagues that have not developed the same level of deep smarts yet. Furthermore, an organization cannot leave it to chance that employees share their deep smarts. They should stimulate their experts to share knowledge with their less knowledgeable colleagues. We refer to this sharing as the pushing of knowledge from the experts to their colleagues, because the people that posses the knowledge take the initiative in sharing their knowledge (Helms & Buysrogge, 2006).

Knowledge that is referred to as deep smarts is typically stored in the employees' heads and hands. This makes this knowledge difficult to share and therefore not every type of knowledge exchange is as effective as another. For example, the exchange of knowledge by means of a presentation is very superficial while the exchange by means of a master – apprentice relationship is very rich. There are several techniques for sharing deep smarts (Leonard et al., 2005), which differ in terms of the *viscosity* of the knowledge that is exchanged. Viscosity is a measure for the richness of the knowledge (Davenport et al., 1998). The different techniques for knowledge transfer that Leonard et al. (2005) distinguish range from *passive reception* to *active learning* and are shown in figure 1. From left to right in figure 1, there is an increase in the viscosity of the knowledge that is exchanged.

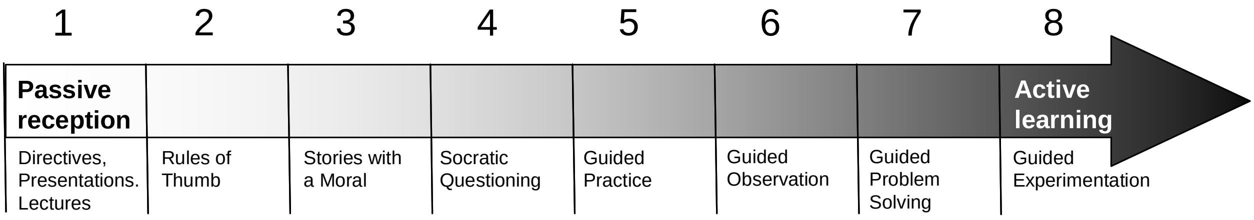

Figure 1: Scale for measuring the viscosity of knowledge

We assume that the knowledge of an employee increases more when more viscous knowledge exchanges take place. Consequently, only a rich exchange of knowledge will substantially contribute to an increase of the expertise level of the receiver.

Summarizing, a push network is a community of people with different expertise levels and the aim to exchange deep smarts from people with a high expertise level to people with a low expertise level such that the expertise level of the latter increases. In the following sections, potential knowledge sharing bottlenecks in these push networks are presented.

Master-apprentice relationships

In a push network it is important that all experts share their knowledge. However, if low viscosity knowledge transfers are used, only superficial knowledge is transferred. Hence, the receiver of the knowledge lacks a deep understanding of the received knowledge and cannot easily apply it. Therefore, we only consider high viscous knowledge transfers suitable for the development of professional skills. In figure 1 it involves the active learning approaches that are labeled 5 till 8. These types of knowledge transfer are very similar to master-apprentice relationships and are characterized by long-term relationship between a master and its apprentice.

From a network perspective an effective push network requires that people with a high expertise level should be connected, i.e. transfer their knowledge to, to one or more people with a lower expertise level. Moreover, this knowledge transfer should be of high viscosity in order to truly transfer deep smarts. If there is no such connection there is no knowledge transfer. Vice versa, people with a low expertise level should have connections, i.e. receive knowledge from, to one or more people with a high expertise level. If there is no such connection they do not receive knowledge and are not developing their professional skills. Preferably, people with a low expertise level should have several connections to people with a high expertise level. Otherwise, they depend on only one person for the development of their professional skills. Because transferring deep smarts takes time it is not very likely that people with high expertise levels can have many high viscous connections to people with lower expertise levels and vice versa. Therefore, the number of high viscous connections should be limited to 3 or 4.

The above can be summarized in the following potential bottlenecks:

Bottleneck 01	People with a high expertise level do not transfer their knowledge with high viscosity to one or more people with a lower expertise level.
Bottleneck 02	People with an expertise level below the highest expertise level do not receive knowledge with high viscosity from at least two people with a higher expertise level.
Bottleneck 03	People with a high expertise level transfer their knowledge with high viscosity to more than four people with a lower expertise level.
Bottleneck 04	People with an expertise level below the highest expertise level receive knowledge with high viscosity from more than four people with a higher expertise level.

Sub-communities

Potentially, it should be possible that any member from a community can be connected to any other member in the community. However, from literature it is known that homophily (Zenger & Lawrence, 1989; Sparrowe, Liden, Wayne, and Kraimer 2001) and geographical spread (Allen, 1977) can be potential barriers for knowledge transfer between people. Homophily refers to the fact that people more easily hook up with people with similar backgrounds. Conversely, people from different backgrounds do not easily connect which constrains the free flow of knowledge in a community. Geographical spread is another barrier for knowledge transfer. Research showed that the probability of knowledge exchange is highest when people are in close proximity to each other. The further people are away, the lower the probability of knowledge exchange. Both homophily and geographical spread can lead to the formation of loosely or disconnected sub communities within in a community.

Sub communities are in itself unwanted because it limits or rules out the transfer of deep smarts between people in different sub communities. To determine the impact of the existence of sub communities, the composition of and the connection between the sub communities should be taken into account. The distribution of expertise over the different sub communities determines whether people with lower expertise levels have easy access to people with higher expertise levels. If there are no people with high expertise levels in a sub community, people rely on high viscous connections to people with high expertise levels in other sub communities for the development of their professional skills. If a sub community lacks experts and also does not have high viscous connections to experts in other sub communities the development of professional skills is in jeopardy.

The above can be summarized in the following potential bottlenecks:

Bottleneck 05	Unbalanced distribution of expertise over sub communities.
Bottleneck 06	Lack of high viscous knowledge transfers between sub communities.

Knowledge drain and knowledge brokers

In every company, employees leave the organization after a certain time. For example, they get a better job elsewhere or because they retire. When an employee leaves the organization this might lead to a potential loss of valuable expertise, something also referred to as ‘knowledge drain’ (Zhuge, 2002; Kiger, 2005), or to disconnectedness of the network. Both can have a negative influence on the development of professional skills in the community.

Whether the departure of a person indeed results in a knowledge drain depends on several factors. First of all, it is obvious that it depends on the expertise level of a person, the higher the expertise level the higher the chance of knowledge drain for the organization. Secondly, it is important to know whether the person transferred his knowledge to other people in the community. If high viscous connections to other people exist, the potential knowledge drain is limited because he transferred his deep smarts to other members in the community. Finally, the influence of a person is also an indicator of the value of a particular employee. Influence involves the number of people that a person reaches in total, either by direct or indirect connections. The more persons are reached the more influential that person is. Hence, one could say that this person’s knowledge and ideas strongly influences the way of working in an organization.

Another effect of people leaving the organization concerns disconnectedness. When a person leaves the organization it does not only lead to a loss of knowledge, but also in a hole in the network. If the person that leaves the organization fulfils a brokerage role between different sub communities, this can potentially lead to the formation of loosely or disconnected sub communities. The types of brokerage roles that can be distinguished include: liaison, gatekeeper, and representative (Fernandez & Gould, 1994). Because a person can have many connections he can fulfill different roles at the same time and can fulfill the same role several times. Consequently, if a broker leaves the organization it does not automatically lead to the disconnection of sub communities because other persons can have similar brokerage with respect to the same sub communities. However, a special case is when the departure of a person leads to the total disconnection of two sub-communities. In that case the brokerage relation is called a *network bridge* (Burt, 1992), i.e. the only connection that exists between two sub communities.

The above can be summarized in the following potential bottlenecks:

Bottleneck 07	Departure of people with a high expertise level with few or none high viscous connections to other people.
Bottleneck 08	Departure of people that influence many people (directly and indirectly) with their knowledge and thinking.
Bottleneck 09	Departure of people that fulfill a brokerage role in the network.

Preparation (The Checklist)

Knowledge Network Analysis is a rather straightforward technique. Nevertheless, some preparation is required to use the technique to its full potential. Several aspects of preparation are discussed below.

Basics of network analysis

Although this chapter describes how to apply Knolwedge Network Analysis, it is not a complete guide in to the basics of network analysis. Therefore, it is recommended that the people who apply the technique read an introduction to social network analysis, which is the foundation of Knowledge Network Analysis. A good introduction to social network analysis can be found at: http://faculty.ucr.edu/~hanneman/nettext/ (Hanneman & Riddle, 2005). Reading chapter 1 thru 5 will provide the reader with the basics of network analysis while chapter 7 thru 17 provide a quick reference to a wide range of different network measures available. Reading this introduction will provide a deeper understanding of social network analysis and hence Knowledge Network Analysis. Furthermore, it can also be used as a quick reference guide during the interpretation of the results. For a complete textbook on Social Network Analysis, however, is referred to Wasserman & Faust (1994).

Survey

The basis for the analysis is network data concerning a community of practice. This data is collected by means of a survey, either on-line, via e-mail or on paper. Although the survey consists of a number of standard questions some customization of the questionnaire is required. The questions itself can be used in any organization. However, it is the answer categories that require some customisation because it concerns a list of people with whom a respondent exchanges knowledge. This list of names is of course different for each organization and needs to be customized.

Communication to the respondents

Members of a community mainly play a role during the data collection phase, i.e. they are the respondents that provide the network data. To ensure the willingness of the respondents to participate in the survey, communication around the project is rather important. There are several ways to announce the Knowledge Network Analysis project, such as company newsletters, community events, or a cover letter that is attached to the survey. In the communication it is also important to address the issue of confidentiality. The analysis reveals the position of employees in a community of practice and this is often considered as sensitive data. Every organization should therefore consider whether it is required to keep data confidential. Of course, the data needs to be disclosed to the project team that analyzes the data. Otherwise it will be impossible to suggest concrete improvements regarding the structure of a community.

Toolkit (The Essentials)

There are two tools required to conduct a Knowledge Network Analysis: a *survey tool* and a *network analysis tool*. A survey tool is required to collect the network data. Although it is possible to collect the data using a paper-based survey, there are several advantages to sending a digital questionnaire via e-mail or using an on-line survey tool. First of all, an digital questionnaire or on-line survey is easier to distribute and secondly it is easier to integrate the results in the format required by a network analysis tool. There are several tools available for conducting an on-line survey. Some suggestions include: SurveyMonkey (www.surveymonkey.com), Free Online Surveys (freeware; freeonlinesurveys.com), and Php Surveyor (open source; www.phpsurveyor.org). In our own practice we are using a digital survey form that was created in Excel.

The network analysis tool is used for quantitative and qualitative analysis of a network. Quantitative analysis involves the application of graph theory to determine certain structural properties of networks that are known from the field social network analysis. A simple example is the shortest path between two people in the network. Qualitative analysis involves the analysis of a visual representation of the network structure and is used to support quantitative analysis. Figure 2 contains a visual representation of a simple network. The nodes represent the people in the network while the lines represent the knowledge transfers between the people. In knowledge transfer there is always a sender and receiver. Therefore, the arrows indicate the direction of the transfer.

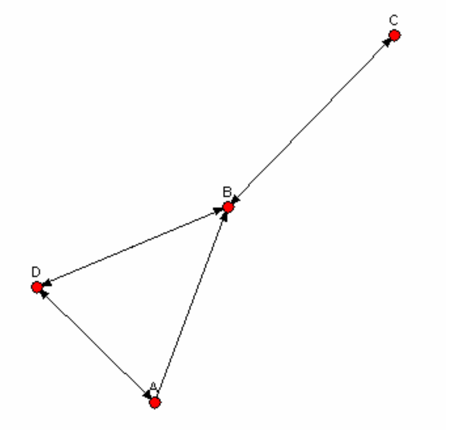

Figure 2: Visual representation of a network.

There are several tools available for network analysis. Some suggestions include: NetMiner (www.netminer.com), UCINET (www.analytictech.com/ucinet/ucinet.htm), and Pajek (vlado.fmf.uni-lj.si/pub/networks/pajek/). We prefer to use NetMiner because of its user friendliness and its visualization capabilities.

Making it Happen (The Approach & the Action)

Data collection and preparation

The data concerning a push network is collected using a survey that is send to each member of the community. Typically, such a survey consists of two parts. The first part focuses on collecting data about the connections between people. The perspective that is chosen is that of the receiver of the knowledge. Hence, the respondent should only indicate from whom he is receiving knowledge. The respondent does not have to indicate to whom he transfers knowledge, because this data becomes automatically available when everybody completes the questionnaire. Besides collecting data about the existence of the connection, data is also collected about the viscosity of the knowledge transfer. An example of how this question looks like in a survey is shown in figure 3.

Name: <enter name>

1. Please indicate how and from which colleagues you receive new knowledge in a structural and organized manner, i.e. not ad-hoc, to develop professional your skills

Options:

1- Presentaties van collega's of externen, richtlijnen, standaarden:
Bij welke van de hiernaast genoemde collega('s) doe je nieuwe kennis op door het volgen van een presentatie of volgen van door hem /haar aangedragen beschreven richtlijnen of standaarden?

2- Rules of thumb:
Welke van de hiernaast genoemde collega('s) vertelt je de vuistregels die gelden voor jouw vakgebied?

3- Stories with a moral:
Van welke van de hiernaast genoemde collega('s) krijg je advies doordat hij /zij een vergelijkbare situatie beschrijft?

4- Socratic questioning (Luisteren, Samenvatten, Doorvragen):
Met welke van de hiernaast genoemde collega('s) doe je nieuwe kennis op door naar hem /haar te luisteren, samen te vatten, en door te vragen?

5- Guided practice:
Met welke van de hiernaast genoemde collega('s) doe je nieuwe kennis op door je werk te doen en dit later met door met hem /haar door te spreken?

6- Guided observation:
Met welke van de hiernaast genoemde collega('s) doe je nieuwe kennis op door met hem /haar mee te kijken en achteraf te bespreken wat hij /zij heeft gedaan?

7- Guided problem solving:
Met welke van de hiernaast genoemde collega('s) doe je nieuwe kennis op door samen met hem /haar problemen op te lossen?

8- Guided experimentation:
Met welke van de hiernaast genoemde collega('s) doe je nieuwe kennis op door eerst zelf na te denken over hoe je bestaande methoden kan verbeteren en dit vervolgens met hem /haar te doen?

1. Please indicate how and from which colleagues you receive new knowledge in a structural and organized manner, i.e. not ad-hoc, to develop professional your skills
Multiple answers for one person are possible. If you do not receive knowledge from a person leave the question open.

A description of the options can be found in the left column!

x1	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
x2	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
x3	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
x4	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
x5	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
x6	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
x7	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
x8	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
x9	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
x10	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
x11	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
x12	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
x13	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
x14	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8
x15	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐8

Figure 3: Example of survey question (some text in Dutch)

The second part of the questionnaire consists of questions to collect demographic data about the respondent. Examples include the name, function, expertise level, and office location of the respondent. Together with the data on the connection this data is required to identify the bottlenecks as presented in the previous section. Bottleneck 01, for example, can only be identified if data is collected about the expertise level of the community members. Some of this data can also be collected from other sources such as the Human Resources Department. It is even preferred to use alternative data sources because it reduces the amount of time that a respondent needs to complete the survey.

After collecting the network data, it should be translated into a matrix representation to make it suitable for network analysis. This is illustrated using the network that was presented in figure 2. This network consists of four members: A, B, C and D, which are referred to as *actors* in KNA. Furthermore, there are six connections between these actors that are referred to as *links*. Figure 4 shows the matrix representation of this network. The names of the actors are shown in the rows and columns of the matrix. Rows indicate the senders of the knowledge and the columns the receivers of the knowledge[1]. Numbers in a cell indicate the weight of a link, i.e. viscosity, between two actors. If the weight of a link is zero there is no link between two actors. The diagonal of the matrix does not contain any numbers because an actor can not have a link to itself. Following this logic, cell (1,2) in the matrix indicates that there is a link from actor A to actor B with a weight 2.

	A	B	C	D
A	-	2	0	4
B	0	-	6	3
C	0	5	-	0
D	2	3	0	-

Figure 4: Matrix representation of network data

The demographic data of the actors are called *attributes* and are stored in a separate table. The rows of this table contain the names of the actors while the columns contain the attributes. Once the network data is collected and prepared it can be entered into a tool which supports network analysis.

Network analysis

The analysis starts with making a visualisation of the network, an example is provided in figure 7 in the Real Cases section. It gives an impression of the structure of the network and helps to interpret the results from the quantitative analysis. After exploring the visual representation of the network, the analysis focuses on the identification of bottlenecks 01 till 09. The identification of these bottlenecks using qualitative and quantitative analysis is discussed in the remainder of this section.

Bottleneck 01: People with a high expertise level do not transfer their knowledge with high viscosity to two or more people with a lower expertise level.

To detect this bottleneck the *out-degrees* of actors is analyzed. The out-degree is a relatively simple measure that counts the number of outgoing links of an actor. To identify bottleneck 01 only out-degrees to actors with a lower expertise level should be counted. Those actors that have an out-degree of zero or one are potential bottlenecks.

Bottleneck 02: People with an expertise level below the highest expertise level do not receive knowledge with high viscosity from at least two people with a higher expertise level.

For detecting this bottleneck the *in-degree* of actors is used. This measure counts the number of incoming links of an actor. To identify bottleneck 02 only in-degrees from actors with a higher expertise level should be counted. Those actors that have an in-degree of zero or one are

[1] It should be noted here that each column in the matrix represents the survey results of a single respondent.

potential bottlenecks. The results of bottleneck analysis 01 and 02 can also be verified in the visualization of the network by counting an actor's outgoing and incoming links respectively.

<u>Bottleneck 03</u>: People with a high expertise level transfer their knowledge with high viscosity to more than four people with a lower expertise level.

To determine these bottlenecks, the out-degree measures from bottleneck analysis 01 can be used again. Those actors that have an out-degree higher than four are potential bottlenecks.

<u>Bottleneck 04</u>: People with an expertise level below the highest expertise level receive knowledge with high viscosity from more than four people with a higher expertise level.

Here we can use the in-degree measures from bottleneck analysis 02 to detect any bottlenecks. Those actors that have an in-degree higher than four are considered potential bottlenecks.

Identification of sub communities

Before starting the analysis concerning bottleneck 05 and 06, the network data should be tested for the possible existence of sub communities. For this purpose the Girvan Newman algorithm is used, which is based on cluster analysis using the *link betweenness* as a clustering function. The link betweenness of a link counts how many times a particular link lies on the shortest path between all other pairs of actors in the network. The clustering process starts by putting all actors in one cluster. Then the link betweenness of all links is calculated and the one with the highest link betweenness is removed. If a link has a high link betweenness this is a possible indication that this link serves as a network bridge between groups of actors. Removing such a link could lead to the separation of a large cluster into one or more smaller clusters. This step is repeated till there are as many clusters as there are actors.

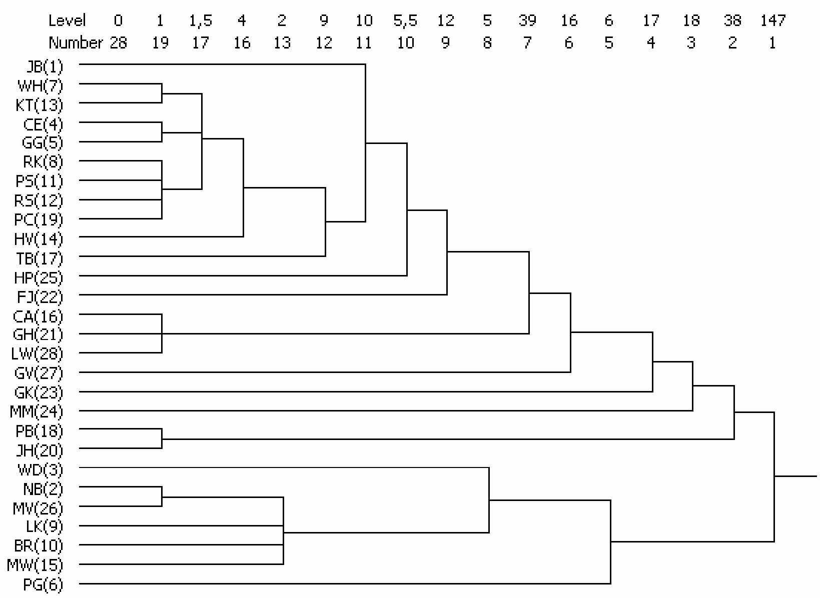

Figure 5: Dendrogram of the push network

The output of cluster analysis is typically displayed in a dendrogram, an example of such a dendrogram is shown in figure 5. On the vertical axis a dendrogram displays the actors and on the horizontal axis it displays the steps in the clustering process. For each step in the clustering process it displays the link betweenness value that lead to the separation of the clusters (level) and the number of communities that exists after the separation (number). The clustering process is shown from right to left in figure 5, the splitting of branches represents the splitting of larger clusters into smaller clusters. In the example, application of the Girvan New algorithm results in

17 alternatives for clustering the actors in sub communities (as many as there as clustering steps). It then comes to picking out the right clustering, which is done using the significance level for each step using statistical analysis. Next, the step with the highest significance level is selected for further analysis. NetMiner supports the Girvan Newman algorithm and is also capable of creating a visualization of the results in which the sub communities are indicated, an example is shown in figure 8.

By examining the function, location and expertise level of each actor in the sub communities it can be verified whether one of these attributes is responsible for the formation of sub communities. This can also be cross checked by calculating the External/Internal (E/I) index of different groups of actors. The E/I index measures the orientation of a pre-defined group of actors and its value can range from -1 (actors only have connections inside the group) to +1 (actors only have connections outside the group). If the value of the E/I index of a group is lower than 0 this group might be a sub community.

<u>Bottleneck 05</u>: Unbalanced distribution of expertise over sub communities.

This bottleneck is detected by a visual inspection of the push network in which the sub communities are indicated. The goal is to determine whether the experts are distributed evenly over the number of sub communities while also taking into account the number of actors in a sub community. If two sub communities are equal in size, both communities are expected to contain approximately the same number of experts.

<u>Bottleneck 06</u>: Lack of high viscous knowledge transfers of experts across the sub communities.

This bottleneck can be detected by calculating the out-degree of experts and to count how many of these links cross the community boundary. In case the links of an expert do not cross the boundary of its sub community, the actors in the other sub communities can not benefits from his expertise. It is of course possible that knowledge of experts is indirectly exchanged to other sub communities via the specialists. Therefore, also the out-degree of specialists should be examined.

<u>Bottleneck 07</u>: Departure of people with a high expertise level with few or none high viscous connections to other people.

Locating experts with few links is done using the out-degree of actors, which already has been calculated for the analysis of bottleneck 01. The departure of experts with zero or one link might result in a knowledge drain.

<u>Bottleneck 08</u>: Departure of people that influence many people (directly and indirectly) with their knowledge and thinking.

The influence of actors is determined by looking at the *reachability* and the *average shortest path* of an actor. The reachability of an actor indicates the number of other actors in the network that this actor can reach directly or indirectly. But if two actors can reach the same amount of actors in the network their influence is not necessarily the same. Their influence is said to be stronger if the distances to these actors are shorter. A good indicator of an actor's average distance to the other actors is the average shortest path. If the average shortest path is high an actor needs many steps and if it is low an actor only needs a few steps to reach other actors in the network. Dividing reachability by the average shortest path leads to an indicator of an actor's influence that takes into account the number of actors an actor can reach as well as its distance from these actors. The indicator is high when the reachability is high and the shortest path is low. Therefore, the departure of experts with a high score on this indicator is a potential loss for the organization.

Bottleneck 09: Departure of people that fulfill a brokerage role in the network

Brokerage roles of actors are determined by their position in the network. The roles that are determined include: liaison, gatekeeper, and representative. A person acts as *liaison* when he connects people in two different groups while he is not a member of either group (figure 6.1). Often a person that connects two groups is part of one of these groups; in that case we speak of a gatekeeper or representative. A person is a *representative* if he is transferring knowledge from members of his sub community to members of other sub communities (figure 6.2). In other words, he is acting as a representative or as a 'spokesman' for his sub community. Finally, a person is a *gatekeeper* if he receives knowledge from other sub communities and transfers that knowledge to members of his own sub community (figure 6.3). As a gatekeeper this person controls the flow of knowledge from other sub communities to the members of his own sub community.

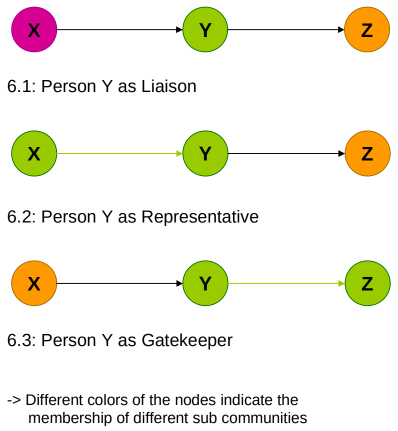

Figure 6: Explanation of different brokerage roles

Because an actor can have many links to different actors, he can fulfill different roles at the same time and can also fulfill the same role several times but for different actors. In NetMiner it is possible to determine the brokerage roles for each actor. Actors that fulfill many brokerage roles can play an important role in the connection between sub communities. The departure of these actors is therefore a potential risk for the organization.

Results & Next Steps (The Follow-Up)

Application of Knowledge Network Analysis results in an indication of possible bottlenecks with respect to knowledge sharing in communities. To validate these results it is important to check if the bottlenecks that are found, match with personal observations and experiences of the community members. After validation of the results, the project team should discuss which interventions are suitable to overcome the observed bottlenecks. Examples of interventions include: changing the organization structure or introducing new reward systems. There is not a simple recipe, meaning that there is a standard intervention for every observed bottleneck, because the selected interventions often depend on the specific context of the organization. Moreover, there is not always a single best solution. Since the possible consequences of the interventions can be quite substantial, the interventions should be approved by management before they can be effectuated.

Results from the interventions can be expected after several months or later because changing the behaviour of people and organizations takes time. To measure if the interventions have been effective one can conduct a second Knowledge Network Analysis. Consequently, it is possible to compare the situation before the interventions with the situation after the interventions. If the desired results have not been achieved the project team has to consider additional interventions.

Real Cases (As it has Happened)

Case study context

The case study discussed in this section concerns a knowledge-driven consulting and engineering firm that is active in the following fields: Infrastructure, Facilities and Environment. Worldwide the organization employs approximately 10,000 people. The regional office involved in the Knowledge Network Analysis is located in the Netherlands and employs a total of 65 people. Employees of the regional office are typical knowledge workers with a master's degree in Architecture, Engineering and Construction. Their main job is the design of and advice on structures in the aforementioned fields of infrastructure, facilities and environment. In the regional office, Knowledge Network Analysis has been applied to analyze the Civil Engineering community. There are 31 people working in this knowledge area, 28 of them filled out the network survey. These 28 people are located in 3 offices in three different cities in the Netherlands, with 18, 9 and 1 people in each office respectively. Furthermore, the community consists of 14 engineers, 11 project leaders, and 3 consultants.

The network data has been collected using a survey, while the required demographic data has been collected with the help of the HRM department. The demographic data involves the: *function*, *location* and *expertise level* of each actor in the community. After collecting the network data it was entered into a network matrix, created in Microsoft Excel, and then imported into NetMiner for further analysis. Additionally, we defined 3 attributes for actors in NetMiner to store information about their function, location and expertise level. The possible values for each of the attributes are shown in table 1.

Table 1: Functions, locations and expertise level at case study company

Functions	Location (# people)	Expertise level
Engineer	Office A (18)	Trainee
Project leader	Office B (9)	Specialist
Consultant	Office C (1)	Expert

After entering all the data in NetMiner we are ready to analyze the effectiveness of the push network. The next section shows how qualitative and quantitative analysis has been used to identify bottlenecks that constrain the effectiveness of the push network at the engineering and consulting firm.

Analysis of push network

The first thing to do is creating a visualization of the network to get an impression of the structure of the network. Figure 7 shows the visualization for the push network of the consulting and engineering firm[2]. The visualization shows the actors and the links between the actors. As mentioned before the focus is on highly viscous knowledge transfers. Therefore, only knowledge transfers with a viscosity of 5, 6, 7 or 8 are shown (i.e. the right side of the scale). Moreover, the visualization also contains information concerning the function, location and expertise level of an actor. This data is coded using the color, size and shape of the actors (see legend of figure 7).

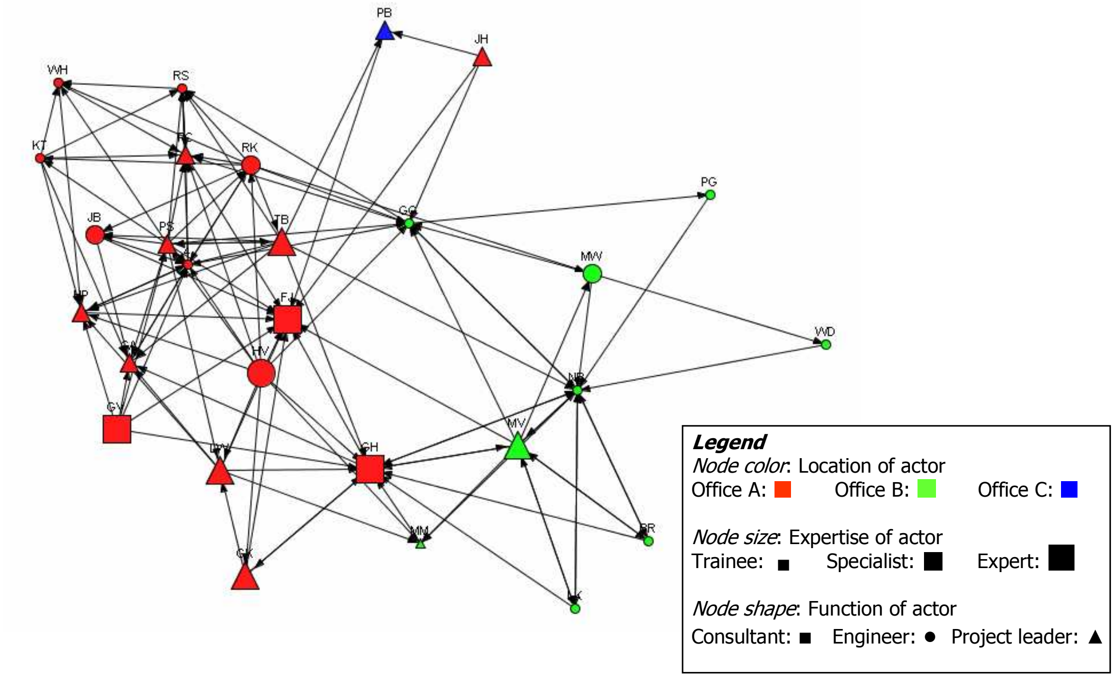

Figure 7 – Visual representation of the push network

In the following each bottleneck is identified individually. After identification of all the bottlenecks the overall conclusions regarding the effectiveness of the push network are presented.

Bottleneck 01: People with a high expertise level do not transfer their knowledge with high viscosity to two or more people with a lower expertise level.

In the case study context this bottleneck implies that knowledge should be transferred from experts to specialists and/or trainees and from specialists to trainees. The results of the out-degree analysis are shown in table 2 and reveal that there are 6 specialists with zero or one outgoing links to a trainee and that there are 2 experts with zero or one outgoing link to a trainee or specialist. In other words, 8 out of 17 actors do not sufficiently transfer their knowledge to less experienced colleagues.

Table 2: Out-degree of actors (only to actors with lower level of expertise)

Actor	CA	HP	JB	JH	MW	PB	PC	PS	RK	FJ	GH	GK	GV	HV	LW	MV	TB
Out-degree	1	1	1	1	3	0	1	5	5	0	2	0	4	7	3	6	8
Expertise level	S	S	S	S	S	S	S	S	S	E	E	E	E	E	E	E	E

[2] The placement of nodes in the visualization is determined by the SpringEd algorithm, which is a fairly straightforward implementation of Eades' Spring Embedder (Eades, 1984). Fundamentally, repelling forces are given to every pair of non-adjacent nodes, and attractive forces are given to every pair of adjacent nodes. Following this spring model, non-adjacent nodes are spread well one the plane and adjacent nodes are placed near each other.

Bottleneck 02: People with an expertise level below the highest expertise level do not receive knowledge with high viscosity from at least two people with a higher expertise level.

This bottleneck implies that trainees should receive knowledge from more than one specialist and/or expert, and that specialists should receive knowledge from more than one expert. The results from the in-degree analysis are presented in table 3. It shows that there are 4 trainees with zero or one incoming link from a specialist or expert and that there are 6 specialists with zero or one incoming link from an expert. Consequently, 10 out of 20 actors are not able to fully develop their professional skills.

Table 3: In-degree of actors (only from actors with higher level of expertise)

Actor	BR	CE	GG	KT	LK	MM	NB	PG	RS	WD	WH	CA	HP	JB	JH	MW	PB	PC	PS	RK
Out-degree	1	8	6	2	1	3	4	0	4	1	2	4	4	1	0	1	1	1	3	1
Expertise level	T	T	T	T	T	T	T	T	T	T	T	S	S	S	S	S	S	S	S	S

Bottleneck 03: People with a high expertise level transfer their knowledge with high viscosity to more than four people with a lower expertise level.

Here we are looking for experts and specialists with too many outgoing links. The out-degree measures in table 2 show that there are 2 specialists and 3 experts with too many outgoing links. One expert even has 8 outgoing links, which might imply that he spends too much time on high viscous knowledge transfer to other actors.

Bottleneck 04: People with an expertise level below the highest expertise level receive knowledge with high viscosity from more than four people with a higher expertise level.

In this case, the bottleneck involves those trainees and specialists that receive knowledge from more than 4 actors with a higher expertise level. The in-degree measures in table 3 again show that there are 2 trainees and 0 specialists with too many incoming links. There is one trainee with 8 incoming links; he is spending too much time on developing his professional skills.

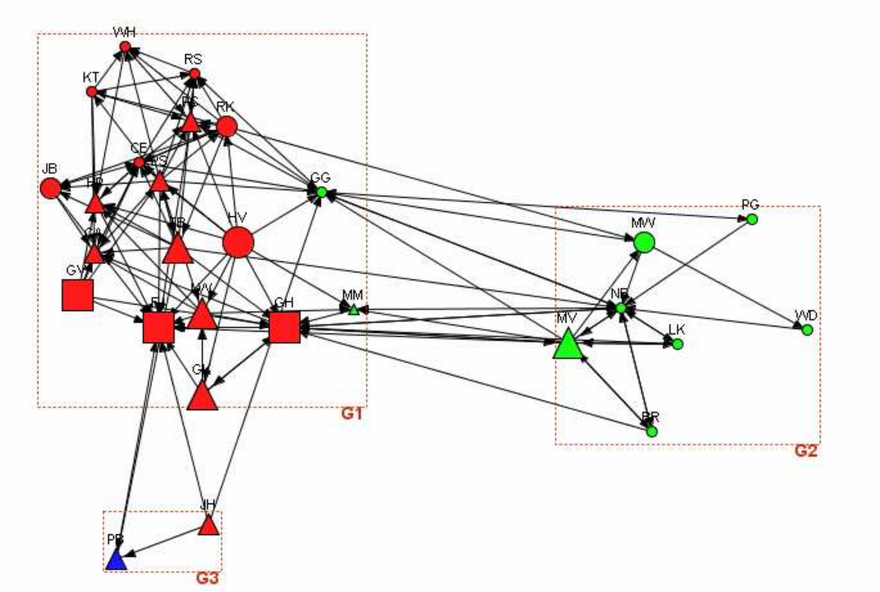

Figure 8: Identification of communities in the push network

Before analyzing bottleneck 05 and 06 it is required to identify any sub communities in the push network. For this purpose, the *Community* function in NetMiner has been used. This resulted in the identification of 3 communities (see figure 8). The communities are labeled G1, G2, and G3, and are indicated by putting a red box around the actors of the community. By looking at the colors one can see that almost all red actors are part of community G1, almost all green actors are part of community G2, and that two actors with very few connections form community G3. The color indicates the office location of the actors, which implies that the spread of actors over the different offices severely limits the knowledge transfer between the actors in these offices.

Furthermore, it implies that the other attributes such as expertise level and function are not a barrier for knowledge exchange. This assumption can be verified by checking the External/Internal (E/I) index of different groups of actors. Figure 9 shows the results of applying the E/I index to different groupings based on location, function, and expertise level. The results clearly show that only the location leads to an internal focus of the actors (i.e. E/I index <0) and is therefore a possible indication for sub community formation.

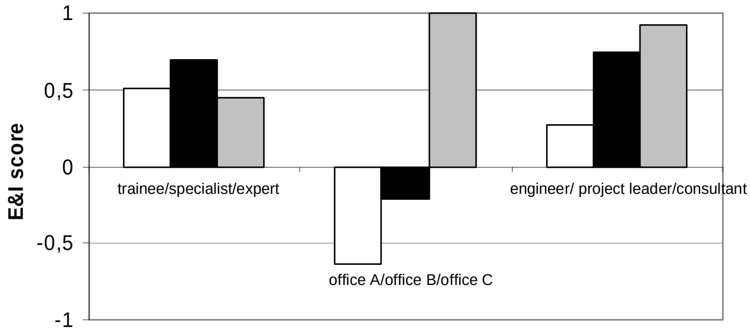

Figure 9: E/I index for different groups of the push network

<u>Bottleneck 05</u>: Unbalanced distribution of expertise over sub communities.

The sub communities become a problem when it results in an unbalanced distribution of expertise over the sub communities. A visual analysis of the network in figure 8 reveals that there is an uneven distribution of expertise, because 7 out of 8 experts are part of community G1. Community G2 has a total of 7 actors but only one expert and one specialist. Finally, community G3 is composed of two specialists. The lack of experts in group G2 and G3 implies that these groups do not receive much knowledge from experts and therefore there is a potential risk that they do not receive valuable knowledge from other communities.

<u>Bottleneck 06</u>: Lack of high viscous knowledge transfers of experts across sub communities.

The unbalanced distribution of experts over the sub communities is only a problem if the outgoing links of experts do not cross the boundaries of their community. The results from the cross boundary out-degree analysis in table 4 show that five experts in sub community G1 do not have high viscous exchanges outside their own sub community. Therefore, actors in other sub communities are cut off from the deep smarts of these experts. Another interesting result is the fact that expert GH only transfers his knowledge to actors outside his own sub community. Consequently, actors from the same sub community do not benefit from the deep smarts of their colleague.

Table 4: Out-degree of experts across community boundaries

Com-munity	Actor	Out-degree	Out-degree across boundary
G1	FJ	0	0
G1	GH	2	2
G1	GK	0	0
G1	GV	4	0
G1	HV	7	0
G1	LW	3	0
G1	TB	8	2
G2	MV	6	4

Summarizing, from the 8 experts there are only 2 experts exchange knowledge outside their own community. On basis of this analysis it can be concluded that the sub communication results in the isolation of the knowledge of experts. It is of course possible that knowledge of experts is indirectly exchanged to other communities via the specialists. However, a similar analysis on the out-degree of specialists revealed that only 1 specialist out of 9 has links that cross the boundary of their sub community.

Bottleneck 07: Departure of people with a high expertise level with few or none high viscous connections to other people.

The analysis of bottleneck 01 revealed that 2 experts and 6 specialists do not transfers their knowledge or transfer their knowledge to just one other actor. Because they do not transfer their knowledge to colleagues, the departure of these actors might result in a knowledge drain.

Bottleneck 08: Departure of people that influence many people (directly and indirectly) with their knowledge and thinking.

The departure of people that are very influential can also be a potential loss for an organization. Table 5 shows the influence of the experts based on their reachability and average shortest path. All experts, except one, reach the majority of their colleagues, i.e. 24 or 25 out of 27. However, only three experts can reach every other actor in two to three steps. Therefore, they are said to be the most influential experts and the possible departure of these experts is a potential loss for the organization.

Table 5: Influence of experts in the network

Actor	Reach (out) to others	Average shortest path	col 2/ col 3
FJ	0	0,0	0,0
GH	24	3,2	7,5
GK	24	3,8	6,3
GV	25	2,5	10,0
HV	25	2,2	11,5
LW	24	3,4	7,1
MV	24	3,3	7,4
TB	24	2,5	9,6

Bottleneck 09: Departure of people that fulfill a brokerage role in the network

The brokerage roles of each actor are determined using the *Brokerage* function in NetMiner. Table 6 shows the number of Gatekeeper, Representative and Liaison roles for each actor. Actors that do not fulfill any of these roles are left out of the table.

Table 6: Brokerage roles of actors in the push network

	GG	RK	TB	GH	NB	MW	MV
Gatekeeper	8	0	0	11	8	2	3
Representative	8	3	4	11	12	0	7
Liaison	2	0	0	0	0	0	0

There are various actors that act as Gatekeepers and Representatives and that there is just one actor that acts as a liaison: GG. Logically, actors that fulfil many brokerage roles are positioned along the border of the communities in figure 8. However, one should be careful with visual analysis because one might easily overlook RK and GG, for instance, which are not located along the border of there community but still act as a broker. Therefore, it is important to support visual analysis always with quantitative analysis.

Communities only become disconnected if there are network bridges between the sub communities. This is only applies to actor TB, when leaves community G3 will not receive knowledge from community G1 anymore. However, conversely community G1 is not disconnected from G3 in case TB leaves because he is not the only Gatekeeper with respect to G3. In the other situations, two or more actors have to leave before sub communities become disconnected. Therefore, from a brokerage point of view the organization is not very sensitive to the departure of only one of the actors in table 6.

Conclusions and recommendations

The bottleneck analysis regarding the effectiveness of the master-apprentice relationships (bottleneck 01 -04) revealed some structural problems in the push network. There are too many experts and specialists that do not or hardly transfer their deep smarts to colleagues. Consequently, too many trainees and specialist do not have enough high viscous relations in order to properly develop their professional skills. The company should address this issue because there is a structural problem in the development of professional skills. It can be easily solved by stimulating more experts and specialists to transfer their knowledge (assuming that their knowledge is relevant and valuable for the organization), because the ratio between trainees and specialists that should receive knowledge and the experts and specialists that can provide this knowledge is almost 1 to 1. Therefore, the constraints posed by bottleneck 01 till 04, with respect to the minimum and maximum number of links, is not a problem in this organization.

Another structural problem was revealed by the bottleneck analysis concerning the existence of sub communities (bottleneck 05-06). The analysis showed that the geographical spread of actors over different office locations is causing the formation sub communities, which is a potential barrier for knowledge exchange. Therefore, we looked more closely to both office locations. The distribution of experts over the sub communities is unbalanced because the majority (7 out of 8) is located in Office A. This is a problem because the experts (and also the specialists) in office A hardly share their knowledge across the boundary of their sub community. Furthermore, visual analysis also reveals that there is a nice mix of functions and expertise levels in office A. While in office B, there is only one expert project leader, one specialist engineer and six trainee engineers. The low level of expertise might be an explanation why employees at office A do not have a need to receive knowledge from their colleagues in office B. Vice versa, office B is very dependent on office A for acquiring new knowledge, which it does not receive. It is recommended that the organization increases the variety of functions and expertise levels at office A and B and at the same time increase the amount of high viscous knowledge transfers between the offices. Both can be realized at the same time by switching employees between office A and B.

The third and last bottleneck analysis focused on the possible risk of the departure of employees which might result in knowledge drain and disconnectedness (bottleneck 07-09). The highest risk is posed by employees that do not transfer their knowledge to colleagues. Because there are 8 employees, 2 experts and 6 specialists, that hardly transfer their knowledge. To determine if their departure will actually lead to a knowledge drain, it is recommended that the organization investigates the relevance and value of the knowledge of these employees before undertaking any action. In case they have valuable knowledge that needs to be shared there are two options. First, the organization can create challenging career tracks and a stimulating work environment so that employees do not want to leave. Secondly, the organization can make sure that these employees have viscous knowledge exchanges with potential successors.

The impact of the departure of influential employees or employees that hold brokerage roles is rather low. Analysis of the influence showed that almost all experts are rather influential. Therefore, the impact of the departure of a single expert is rather low. Furthermore, the risk of disconnectedness is also rather low, because of the redundancy in the brokerage roles between the communities. If one employee leaves this does not immediately lead to disconnectedness, except for actor TB because he acts as a network bridge between sub communities G1 and G3.

Tips & Tricks (To-Do)

- ☑ Get management support for the Knowledge Network Analysis and let management invite/urge community to participate in the survey. This assures high response rates for the survey (higher than 90% is required)
- ☑ Check the conclusions with the actual situation within the organization and personal experience of community members. Contextual information is often required to draw the right conclusions from the findings.
- ☑ Include e-learning systems as actors in the network to study the contribution/dependency of information technology in developing professional skills.

Potholes (Not-to-Do)

- ☒ Do not depend on the visual analysis alone, you easily overlook something. Always support visual analysis with quantitative analysis.
- ☒ Do not draw conclusions on networks if there is a low participation rate of community members in the Knowledge Network Analysis. If too many people are not participating you easily get a distorted snapshot of the situation.
- ☒ Do not use the type of survey questions, as presented in this chapter, in case of large networks (say larger than 75 people). For larger groups alternative data collection strategies should be used.
- ☒ Do not use results of Knowledge Network Analysis to evaluate the performance of employees. A snapshot of the push network does not provide an overall picture of a person’s performance and it only shows the situation at a certain point in time.

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