Knowledge Transfer in a Multiple Virtual Communities Network

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Abstract

Virtual knowledge communities (VKCs) produce and embrace priceless, and often, very unique knowledge assets within the boundary of each virtual community. An important question is how do we maximize the collateral benefits from these valuable assets at the entire VKCs network level? Relying on the graph theory, this study is to investigate how the structure of virtual knowledge network formed by knowledge transfer agents tying two communities and the knowledge profile of each VKC influence the dynamics of knowledge flow in a virtual knowledge community network (VKCN). We found that knowledge will be more efficiently disseminated when knowledge agents are uniformly distributed across the network. Furthermore, we found that an increase of VKCN complexity is maximized when a new knowledge agent is placed between two communities with the minimum information flow. The results of this study will help understand the inter-community knowledge transfer dynamics in virtual knowledge community networks.

1. Introduction

One interesting phenomenon by the Internet is that while it has provided a great deal of opportunity to acquire necessary knowledge, acquiring knowledge has become a complex process. It is particularly true when necessary knowledge is found in external networks beyond the organizational boundary. There are millions of virtual knowledge communities (VKCs) in the world and each VKC creates and embraces priceless, and often, very unique knowledge assets within the boundary of each virtual community. During the last two decades, many research and development organizations engaging innovative tasks began an obvious and swift transformation toward using virtual communities rather than relying on face-to-face interaction [1]. In this context, important questions are; how do we locate necessary knowledge?; and how do we maximize the collateral benefits from these valuable assets at the entire VKCs network level? This study attempts to respond to these questions using theoretical frameworks of knowledge management and mathematical modeling approach.

1.1. Importance of Virtual Knowledge Communities (VKC)

Knowledge is considered one of the most valuable resources for organizational growth and sustained competitive advantage due to its unique characteristics such as intangibleness, difficult transfer, and complex organizational embedment [2, 3]. Because organizations do not have all knowledge necessary within their organizational boundaries, they need to somehow search for outside knowledge sources. One efficient way of acquiring knowledge from external source is to utilize virtual communities.

We define a virtual knowledge community as a virtual community in which knowledge users co-create and share knowledge. The notion of a VKC focuses on a knowledge-centric virtual community where a group of knowledge workers with common topics, interests, problems, experiences and practices co-create and share valuable knowledge. An important feature of knowledge communities is that people bring knowledge and knower in one virtual place equipped with knowledge databases over networks. The combination of these two notions, knowledge and virtual communities, constitute the core elements of VKCs.

VKCs operate on relational structures or networks. People exchange and share knowledge interactively, often in non-routine, personal, and unstructured ways, as an interdependent network. Being free from the constraints of hierarchy and organizational rules, individuals benefit from a VKC by gaining access to new knowledge, expertise, and ideas, all of which may not be available within the organizational boundary [3].

Recently, researchers have paid enormous attention to VKCs due to its tremendous potential for
efficient knowledge creation and transfer [1, 4]. Given the importance and potential of knowledge transfer, researchers have investigated various phenomena within the boundary of a VKC [3, 5, 6]. Furthermore, in research and development communities, the importance of inter-community knowledge transfer has been highlighted due to the emerging need of cross-disciplinary knowledge collaboration [7, 8].

The implications of studies in this area, however, are limited because they merely focus on the knowledge sharing process at nodal (focusing on the behavior of a single community) or dyadic (focusing on the relational behavior of a pair) levels. It is important to note that knowledge creation and transfer activity are no longer bounded within a community, but have evolved into further sophisticated forms of transfer through cross-community knowledge network systems. As cross-community knowledge flows become more complex with an increasing number of VKCs, it is imperative to understand the dynamics of VKC from a macro perspective [5].

Among various issues of VKCs, overlooked but important is the dynamic impact of knowledge flow between two VKCs on the growth of network efficiency of the entire virtual community knowledge network (VKCN). In this study, the network efficiency is measured by network complexity, which is a generalization of the number of spanning trees in a graph. This notion of network efficiency is applied in the quantification of information flow by Stephenson and Zelen [9].

We view a VKCN as an organic social network formed with two apparent entities: 1) a group of VKCs and 2) inter-community knowledge transfer agents who connect any two VKCs by transferring knowledge between the two. We argue that distribution of the agents is an imperative determinant of knowledge transfer efficiency and knowledge accessibility of a VKCN.

Relying on the graph theory, we investigate how network structure formed by knowledge transfer agents tying two communities and the knowledge profile of each VKC influences the dynamics of knowledge flow in a virtual knowledge community network (VKCN). Our objective is to assess the impact of network structure determined by distribution of knowledge agents and common knowledge on knowledge transfer and diffusion. The efficiency of a VKCN is measured by network complexity and the effectiveness of knowledge profile by common knowledge each community has accumulated.

We next review relevant literature, focusing primarily on the theory of knowledge management and social network. We then provide our formal propositions related to the efficiency of inter-community knowledge transfer and mathematical proofs. Finally, we lay out and discuss the results and conclude with contributions, implications and limitations of this research.

2. Theoretical Background

2.1. Knowledge Transfer from the Theory of Knowledge Management Perspective

According to studies of knowledge management, the process of knowledge transfer can be divided into two stages from the perspective of a knowledge transfer agent: 1) understanding (or internalizing) knowledge from a knowledge sourcing VKC, and 2) explaining (or externalizing) it to a knowledge seeking VKC [10, 11] (Figure 1). The characteristics of knowledge agents are crucial in the course of knowledge transfer for this reason. Because understanding and explaining knowledge requires fundamental knowledge of routines, culture, or norms of both VKCs (which is called common knowledge below), it is knowledge transfer agents who enable and facilitate knowledge transfer between the two. It is worth noting that this notion of common knowledge also has been viewed as absorptive capacity of knowledge recipients [12, 13].

![Figure 1. Decomposition of Knowledge Transfer](image)

2.2. Theory of Common Knowledge

From the perspective of inter-community knowledge transfer, knowledge owned by a VKC can be divided into two types: 1) private knowledge that is owned only by one VKC privately and is possibly to be transferred to any possible recipient communities, and 2) common knowledge that is
commonly owned by both interacting communities (see Figure 2).

Social science researchers have been emphasizing the important roles of *common knowledge* in knowledge transfer [14-18]. Common knowledge 1) allows VKCs to share rules in the form of practices, like how to successfully manage knowledge, as well as the fundamental knowledge required to absorb more sophisticated forms of knowledge, and 2) facilitates knowledge transfer activities by increasing similarity of knowledge profiles of the two VKCs.

Transferring knowledge can be costly, particularly when knowledge is being transferred across multiple VKCs that may not have a high level of common knowledge [19]. In this sense, common knowledge brings forth a VKCN that is accessible to all VKCs and lends itself to knowledge development. After all, once knowledge is transferred from one VKC to another, transferred knowledge becomes common of the two, and in turn the amount of common knowledge increases. It is, therefore, important to understand the dynamic effects of common knowledge, and the facilitating mechanism for knowledge transfer.

### 2.3. Structural Centrality in Social Network

We use *Structural Centrality in Social Network* [20] as the framework of analysis for a *virtual knowledge community network* (VKCN). Since the idea of network centrality as applied to human communication was originally introduced by Bavelas [21], the concept has been used to examine various phenomena of social networks such as political integration [22], design of organization [23], diffusion of technology innovation [24, 25], inter-organization relationships [26], group stability [27], network structure in virtual organization [28], and individual centrality in virtual groups [29].

Based upon the theoretical framework of *Structural Centrality in Social Network*, we define a VKCN as a structural collection of VKCs. A simple example of VKCN is presented in Figure 3. Members in each community create and share knowledge within the boundary, developing their own community knowledge profile focusing on a domain knowledge space. We call this virtual place "*Virtual Knowledge Community*" (VKC). In addition, there are members who acquire common knowledge of two VKCs, and transfer knowledge between the two. Wasserman and Faust [30] defined them as *stars*, and stressed the important roles of stars as knowledge transfer agents in the context of inter-community knowledge transfer (Figure 2).

In Figure 1, a VKCN consists of nodes and a set of arcs connecting pairs of nodes, where each node represents a VKC and each arc indicates (possibly multiple) knowledge agents connecting two VKCs. When two nodes are directly connected by an arc, knowledge can be transferred through knowledge agents. Stars in a VKCN are important in that 1) they are the “links” between VKCs that they are associated with, and 2) they are the agents of knowledge transfer between VKCs. We intend to investigate the effects of various stars characteristics on knowledge transfer in VKCN. Weights can be assigned to each arc, which indicate various characteristics of stars including the number of stars, closeness, and communication density.

### 3. Modeling Virtual Knowledge Community Network (VKCN)

#### 3.1. Graph Theory

One of the most useful methods in analyzing and
representing a network is the graph theory. We view a VKCN as a network that consists of nodes representing a VKC and arcs representing knowledge transfer agents between two VKCs. While the graph theory has been viewed as a useful tool in many areas such as computer network research (c.f. [31, 32]), electrical engineering (c.f. [33]) and medical sciences (c.f. [34]), this connection topology has been adopted as in social network analysis for many reasons [35]. One, graph theory offers convenient terms and labels that denotes many properties of social network structure. These terminologies also provide us a set of fundamental tools that allows us to examine the dynamics of those properties. Two, graph theory grants useful mathematical operations and notions with which many of social network properties can be quantified and measured. Finally, the theory allows us to prove theorems about graphs, and hence, about representations of social structure.

In addition to its utility as a mathematical tool, graph theory gives us a representation of a VKCN as a model of a knowledge diffusion system consisting of a set of VKC and knowledge transfer agents between them. By the model, we mean a simplified representation of a small-world VKCN that contains important properties.

### 3.2. Complexity of \( N \)

The efficiency of intercommunity knowledge transfer in VKCN can be measured by the complexity of \( N \) [9]. The complexity, \( c(N) \), of a VKCN \( N \) is to compute the number of possible ways to connect all existing VKCs without a recursive loop. We assume that \( N \) is non-directed, which means we assume that the flow of knowledge is bi-directional. When the weights of every arc\(^2\) in \( N \) is 1, \( c(N) \) counts the number of possible loop-free spanning trees each of which forms a set of arcs connecting all nodes in the graph (c.f. West [37] for details).

Knowledge becomes more valuable and efficient when it is distributed evenly to knowledge users in the network [38]. From this perspective, network complexity is a meaningful measure of knowledge distribution, which indicates the efficiency of knowledge transfer in a network. The complexity of a network is a generalization of the number of spanning trees in a graph. It is a general measure for the cohesiveness of the network, and it also measures the extent to which the stars are evenly distributed throughout the network.

The implication of network complexity is that the greater \( c(N) \) of a VKCN is, the more knowledge traverses through the network. For example, consider a small-world VKCN \( N \) formed by three communities \( C_i, C_j, \) and \( C_k \) with three knowledge agents (presented as three weighted arcs) connecting them. Let \( w_{ij} \) represent the number of knowledge agents between \( C_i \) and \( C_j \). Then, the complexity of \( N \) is defined as

\[
c(N) = w_{12} \cdot w_{23} + w_{23} \cdot w_{31} + w_{31} \cdot w_{12} \quad (1)
\]

where \( w_{ij} = w_{ji} \) because \( N \) is non-directed. The first term \( w_{12} \cdot w_{23} \) of equation (1) is the number of ways to connect all of \( C_i, C_2, \) and \( C_1 \) by connecting \( C_i \) and \( C_2 \) and connecting \( C_2 \) and \( C_3 \). Two other terms can be interpreted in a similar manner.

#### 3.2.1. Complexity of Weighted Network

For a general VKCN \( N \), its complexity \( c(N) \) can be computed as follows. Suppose there are \( n \) VKCs in \( N \) given by \( \{C_1, C_2, ..., C_n\} \). The knowledge agent between \( C_i \) and \( C_j \) will be denoted by \( e_{ij} \) and its weight by \( w_{ij} \). Hence there are \( n(n-1)/2 \) possible arcs (knowledge agents) in \( N \). Even when there is no communication channel between some pair of nodes, we will regard those two nodes being connected by an arc with a weight of 0.

Define the Laplacian matrix \( L(N) \) of the network \( N \) to be the \( n \times n \) matrix, whose \( n^2 \) entries are denoted by \( L_{ij} \) \((1 \leq i, j \leq n)\) such that each diagonal entry \( L_{ii} \) equals the sum of the weights of all arcs that are connected to the node \( C_i \) and each \( L_{ij} \) \((i \neq j)\) equals \(-w_{ij}\) [39]. Now, let \( L_0(N) \) be the \((n-1) \times (n-1)\) matrix obtained by deleting one arbitrary row and one arbitrary column of \( L(N) \). Then we define \( c(N) \) to be the absolute value of the determinant of \( L_0(N) \). When the weights of the arcs in \( N \) are non-negative integers and represent the multiplicities of the arcs, \( c(N) \) is the number of spanning trees in \( N \) [40].

Alternately, \( c(N) \) for a weighted VKCN can be described as follows. Let \( T \) be a spanning tree in \( N \). The complexity \( c(T) \) of \( T \) is defined as the product of all weights in \( T \). Note that \( c(T) \) is a square-free monomial of degree \( (n-1) \) in \( w_{ij} \)'s as variables. Then, \( c(N) \) is the sum of \( c(T) \) over all spanning trees \( T \),

\[
c(N) = \sum_{T \in \beta(N)} c(T) \quad (2)
\]

where \( \beta(N) \) denotes the set of all spanning trees in \( N \).

Clearly, \( c(N) \) is a square-free homogeneous symmetric polynomial of degree \( (n-1) \) in \( w_{ij} \)'s. \( c(N) \) is

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\(^2\) For future investigations, the weight of an arc can be any characteristics of stars involving two communities. In this study, we use the weight of arc as a measure counting the number of stars between two communities.

\(^3\) \( w_{ij} \cdot w_{ji} \cdot w_{ji} \) is not included in Equation (1) because it creates a loop among \( C_i \)'s.
3.3. Growth Dynamics of $c(N)$

3.3.1. Optimization of $c(N)$. If we have a certain amount of knowledge, how do we maximize the benefits to whole VKCN by optimizing knowledge flow efficiency? In this subsection, we will discuss a general guiding principle to optimize $c(N)$ and the dynamic behavior of $c(N)$ under changes in the weights of the arcs (the number of knowledge agents) in $N$. We obtain the total number of knowledge agents by summing all weights of the arcs.

**Theorem 1.** Suppose the total weight of $N$ is bounded. Then, network complexity, $c(N)$, will be maximized when the weights are uniformly distributed among all arcs in $N$. That is, assuming that the number of knowledge agents is bounded, more knowledge traverses through a VKCN when knowledge agents are uniformly distributed across the network.

**Proof.** Since $c(N)$ is a square-free homogeneous symmetric polynomial of degree $(n-1)$ in $w_{ij}$'s, it follows that each partial derivative of $c(N)$ is a square-free homogeneous polynomial of degree $(n-2)$. Since the total weight is bounded, we assume the constraint $g(N) = \sum_{1 \leq i < j \leq n} w_{ij} = C$ for some constant $C$. By Lagrange Multiplier method, finding the maximum of $c(N)$ with this constraint requires solving the following equation involving the gradients: $\nabla c(N) = \lambda \nabla g(N)$. Since $\nabla g(N) = <1, 1, ..., 1>$, it follows that all partial derivatives of $c(N)$ need to be equal, which will be the case when all weights in $N$ are equal.

The implication of Theorem 1 is that when the total number of knowledge agents in a VKCN remains constant, the network complexity is maximized when knowledge agents are evenly distributed throughout the network.

3.3.2. Growth dynamics of $c(N)$. With Theorem 1 as a guiding principle, natural questions are 1) what is the most efficient way to achieve uniform distribution of agents?, and 2) among those, which agent would be more important than others in enhancing knowledge flows? In order to answer these questions, we need to review the notion of knowledge flow between two nodes in a network, and we rely upon the seminal article by Stephenson and Zelen [39] for the definition of and methods for computing the information flow.

For the purpose of this study, we introduce a modified notion of information flow showing the change of the network complexity caused by merging two VKCs.

![Figure 4. VKCN After merging two VKCs (VKC1 and VKC4) from Figure 1](image)

As shown in Figure 4, one interesting phenomena found in a VKCN is merge of two communities (In Figure 3, C1 and C4 merge into C1'). Due to the frictionless nature of virtual organization [41], VKCs can merge in the process of improving the efficiency of knowledge flow. As a matter of fact, merge and split of virtual organizations causes a marginal increase in cost, but offers substantial benefits when compared with the ones of offline organization [42, 43]. Let $N/e_{ij}$ denote a new VKCN with $n-1$ VKCs after merging $C_i$ and $C_j$. The knowledge agent between the two, $e_{ij}$, is no longer present, while all other agents remain active. Let $I_{ij}$ be the knowledge flow between two nodes $C_i$ and $C_j$ in $N$.

**Lemma 2.** The knowledge flow between two communities $C_i$ and $C_j$ in a VKCN $N$ is the ratio of the complexity of $N$ and that of $N/e_{ij}$. That is, $I_{ij} = c(N)/c(N/e_{ij})$ (3)

**Proof.** Available upon request.

Using Lemma 2, we can offer the following theorem which provides an answer to the above questions. The proof is based on a new interpretation of $I_{ij}$ as the inverse of the relative growth rate of $c(N)$ with respect to $w_{ij}$.

**Theorem 3.** An increase of VKCN complexity is maximized when a new knowledge agent is placed between two communities with the minimum information flow.
Proof. By replacing \( N \) with \( N/e_{ij} \) in equation (2), we obtain
\[
c(N / e_{ij}) = \sum_{T \in T(N / e_{ij})} c(T')
\]
where the sum is over all spanning trees \( T' \) in \( N/e_{ij} \). Note that \( w_{ij} \) does not appear in any \( c(T) \). There is a natural bijective matching between the set of all spanning trees \( T \) in \( N \) that contain the arc \( e_{ij} \), denoted by \( \beta(N, e_{ij}) \), and the set \( \beta(N/e_{ij}) \): the matching is given by \( T \rightarrow T/e_{ij} \). Hence, we have,
\[
c(N / e_{ij}) = \sum_{T \in T(N / e_{ij})} c(T / e_{ij})
\]
(4)
Since \( c(T) = w_{ij} \cdot c(T/e_{ij}) \) for each \( T \in \beta(N, e_{ij}) \), we have
\[
\partial_{w_{ij}} c(T) = c(T / e_{ij})
\]
Furthermore, it is clear that \( \partial_{w_{ij}} c(T) = 0 \) if \( T \not\in \beta(N, e_{ij}) \) because such \( T \) will not contain \( w_{ij} \). Therefore,
\[
\partial_{w_{ij}} c(N) = \sum_{T \in T(N / e_{ij})} \partial_{w_{ij}} c(T) = \sum_{T \in T(N / e_{ij})} \partial_{w_{ij}} c(T) = \sum_{T \in T(N / e_{ij})} c(T / e_{ij}) = c(N / e_{ij})
\]
(5)

From Lemma 2 and the fact \( c(N/e_{ij}) = \partial_{w_{ij}} c(N) \), we conclude that \( I_{ij} \) is minimum (among all dyadic information flows), if and only if \( \partial_{w_{ij}} c(N) \) is maximum (among all partial derivatives of \( c(N) \)), which means that growth of \( c(N) \) is to be maximized when an additional knowledge agent is placed between \( C_i \) and \( C_j \) with minimum \( I_{ij} \).

A VKCN, like other information technologies [44, 45], can generate economies of scale through both the creation of new, deeper knowledge and dedicated knowledge agents, which eventually enhance the quality and efficiency of knowledge transfer between two VKCs. This is achieved by a better understanding of culture, norms, and common knowledge of the two VKCs through direct and indirect experiences of knowledge transfer, which in turn lead to qualitatively better knowledge transfer activities. The cost for placing a new additional knowledge agent between two VKCs, therefore, will be lowered as the number of agents between the two increases thanks to the externalities among the agents and related communities [46, 47].

3.3.3. Improving information flow efficiency by merging two VKCs. When there are a considerable number of knowledge transfer taking place between two VKCs, merge of the two may improve the cost of knowledge transfer without causing traffic overload in the network. By reformulating Equation (3), we can obtain an optimal point at which it is better for two VKCs to merge, providing benefits to the entire network.
\[
c(N/e_{ij}) = (V / I_{ij}) \cdot c(N)
\]
(6)
As such, the merge of two communities will decrease the network complexity if \( I_{ij} > 1 \), but will increase when \( I_{ij} < 1 \). This implies that when the interaction between two communities is low, merging the two may increase the overall benefit of the network.

3.4. Indirect Communication vs. Reachability

The knowledge flow \( I_{ij} \) between two VKCs, \( C_i \) and \( C_j \), can be generated from two different activities: direct communication and indirect communication. The indirect communication takes place when there are paths of length 2 or larger between the two nodes, and the transfer of knowledge through these paths is achieved indirectly through other nodes. For example, the paths of indirect communication from \( C_1 \) to \( C_2 \) may include \( C_1 \rightarrow C_3 \rightarrow C_2 \) and \( C_1 \rightarrow C_4 \rightarrow C_2 \) (Figure 1). The information flow through direct communication between \( C_i \) and \( C_j \) is represented by the weight \( w_{ij} \) of the arc \( e_{ij} \).

We can represent the knowledge flow through indirect communication by
\[
\hat{w}_{ij} = I_{ij} - w_{ij}
\]
(7)
That is, \( \hat{w}_{ij} \) denotes indirect flow. The significance of the indirect flow is that it represents the effect of network externality on knowledge transfer. So it is reasonable to expect that \( \hat{w}_{ij} \) should be computable without any reference to the direct flow \( w_{ij} \). The following proposition gives an expression of \( w_{ij} \) that is independent of \( I_{ij} \) or \( w_{ij} \). In the following proposition, \( N/e_{ij} \) indicates a new network after deleting \( e_{ij} \) from \( N \).

Proposition 4. The knowledge flow by indirect communication between two communities \( C_i \) and \( C_j \) in a VKCN, \( N \), is the ratio of the complexity of \( N/e_{ij} \) and that of \( N/e_{ij} \). That is,
\[
\tilde{w}_{ij} = \frac{c(N \setminus e_{ij})}{c(N / e_{ij})}
\]
(8)
Proof: Applying the Deletion-Contraction Recursion [48], the network complexity, \( c(N) \), becomes
\[
c(N) = w_{ij} \cdot c(N/e_{ij}) + c(N/e_{ij})
\]
(9)
Applying Equation (9) to (3), we obtain
\[
I_{ij} = w_{ij} + c(N/e_{ij}) / c(N/e_{ij})
\]
(10)
Now the result follows from \( \tilde{w}_{ij} = I_{ij} - w_{ij} \).

Note that if all communities in \( N \) are reachable, then \( c(N/e_{ij}) \neq 0 \), because \( N/e_{ij} \) remains connected and the complexity of a connected network is positive.
Hence, Proposition 4 implies that $\tilde{w}_{ij}$ will be zero iff $c(N/e_{ij}) = 0$, which happens only when $N/e_{ij}$ is no longer a connected network. An arc (or a knowledge transfer agent) in $N$ will be called essential to $N$ if its (hypothetical) deletion partitions a VKCN. (A technical term for an essential arc representing the essential agent is an isthmus). We summarize this discussion in the following corollary.

**Corollary 5.** The following conditions are equivalent:

i. $\tilde{w}_{ij} = 0$.

ii. $I_{ij} = w_{ij}$.

iii. The communication between $C_i$ and $C_j$ is essential to $N$.

iv. The deletion of the communication channel through $e_{ij}$ results in a disconnected network.

### 3.5. Common Knowledge and Network Complexity

When knowledge is transferred by an agent that does not understand the context of both knowledge sourcing and seeking communities, transferred knowledge may be neither useful nor valuable [29]. What is necessary, therefore, is a better understanding of the optimal condition in terms of the amount of common knowledge, under which a knowledge agent performs best in a VKCN.

Let the contraction $N/e_{ij}$ represent a VKCN after merging two communities $C_i$ and $C_j$. By taking an inverse form of Lemma 2, we obtain,

$$\frac{1}{I_{ij}} = \frac{c(N/e_{ij})}{c(N)}$$

(11)

This suggests that the merger of two communities will increase the network complexity if $I_{ij} < 1$. Alternatively, if the amount of total knowledge transfer between $C_i$ and $C_j$ decreases, then $I_{ij}$ will decrease and the relative complexity of $N/e_{ij}$ compared to that of $N$ will increase. Hence, merging $C_i$ and $C_j$ may increase the overall benefit of the network.

Additional determinants of $I_{ij}$ are the decreasing amount of knowledge topics to be transferred and increasing amount of common knowledge. Consider two VKCs with $n$ private knowledge topics$^4$ in each and with no common knowledge topic (c.f. Figure 2). Before the first knowledge transfer, the number of private knowledge topics for potential knowledge transfer between the two is $2n$. As knowledge transfer takes places, the amount of private knowledge will decrease as the amount of common knowledge increase, and the increasing amount of common knowledge will progressively facilitate the next transfer (After all, the process of knowledge transfer can be viewed as compilation of common knowledge between the two VKCs) (Figure 5).

However, after substantial amount of knowledge of both VKCs are transferred (after a certain point (A)), the knowledge profiles of $C_i$ and $C_j$ turn more similar, there will be less knowledge to be transferred, and thus it will lower $I_{ij}$. Eventually, all topics will become common knowledge and there will be no topics to be transferred.

To demonstrate this phenomenon, we will let $w_{ij}$ vary in a function of the amount of common knowledge, while the number of all knowledge agents in $N$ (excluding the ones between the two VKCs) remains constant. The following graph shows the “local” effect (Figure 4) of the change in common knowledge on the weight of $e_{ij}$ (the amount of direct knowledge transfer between $C_i$ and $C_j$) and the “global” effect (Figure 6) on $1/I_{ij}$ (the ratio of the complexity of $N/e_{ij}$ and that of $N$).

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$^4$ It is assumed that there is no additional knowledge topics created in the two VKCs.
tasks began an obvious and swift transformation toward using VKC [1]. Recently, the speed of organizational transformation has been considerably improved.

The importance of VKCN cannot be overstated. When well structured, it would play as one of the most efficient tools for locating and transferring knowledge. The real power of a VKCN is that it creates opportunities for knowledge workers to go beyond interaction with content and people. Even more dramatic is the amount and availability of knowledge that is offered when people are in need. Contributing and accessing reliable content is just one side of the coin. Combining content management with cross-organizational online collaboration, at all levels of the business, can help unite a company and give it greater insight and perspective, which exponentially increases the value of intellectual capital [49]. We believe that successful formation of knowledge community built on active knowledge providers will significantly increase the benefits and decrease the costs to knowledge workers.

Our VKCN model seeks to advance our understanding of knowledge transfer in virtual community networks in several ways. First, while extant research on knowledge transfers tends to focus on sharing activities within a community, we consider knowledge transfer dynamics among multiple community network level. Second, one common assumption of the studies in this area is that knowledge transfer based on a direct relationship. In this study, we also considered knowledge transfer through indirect relationships which is set by beyond first-tier relationship.

Our macro perspectives on VKCN are differentiated from within-community perspectives by three points. One, the prior notions of social network have mainly focused on the interaction at an individual level within a single community boundary, and thus offer limited information to the case of VKCN. Consider VKCs based on USENET or LISTSERV in which communication is always broadcasted to all members in the community. The application of social network in this context does not provide much information with respect to the dynamics of inter-community knowledge transfer. The relationships between/among VKCs are explicitly constrained by knowledge agents who participate in multiple VKCs. As such, it is wise to apply social network theories at a community level.

Two, despite the enormous benefits of VKCN, the success and failure of the communication technologies depends crucially on the social context in which they are used [29]. Common knowledge accumulated in an organizational boundary has been regarded as the organizational memory or learning capacity [50]. While prior studies in virtual communities have focused merely on quantity of knowledge transferred relying on network structure, it is an innovative attempt to consider the role of common knowledge of virtual communities as learning/understanding capacity of transferred knowledge [12]. We have taken into account the role of common knowledge of virtual communities in the knowledge transfer process.

Finally, one unique phenomenon in the evolution process of a VKC is that they merge and split to improve the efficiency of the network. We consider the effects of these VKC activities on knowledge transfer.

The result of this study provides a set of important implications regarding virtual knowledge community networks. Theorem 1 may be used as a general guiding principle towards maximizing the complexity of a network. It concludes that, in order to uniformly distribute knowledge across the network, a new knowledge agent may be added between two VKCs with the minimum number of agents. However, this may not be sufficient to warrant the most efficient status of the network. The new knowledge agent should be placed where information flow is at minimum.

We believe that network complexity and information flow are vital indicators for the efficacy of a VKCN. There are conventional complexity and centrality measures devised from the perspective of offline individual network [9, 30, 35, 51]. However, the applications of these measures are limited to the offline network as they do not consider critical factors of knowledge-centric virtual communities. More importantly, these measures were designed to be used at an individual level. We attempted to develop new VKC-level assessment methods based on VKC-level measures such as network complexity and knowledge flow. In addition, the effects of network complexity on the efficiency of knowledge flow in VKCN were examined. The validity of developed measures needs to be empirical tested in future research.

To our knowledge, this is the first study employing the notion of the network theory in the context of a VKCN. We attempted to expand and further develop the theory of virtual knowledge communities from the perspective of the macro level, intercommunity knowledge transfer. This new perspective on knowledge creation and transfer across virtual communities should be important not only because it offers a macroscopic view of knowledge economics, but also because it provides a
new opportunity for modern society to speed up the process of interdisciplinary knowledge creation.

5. References


