

Implementing Closeness Centrality Measurements on Workflow-Supported Enterprise Social Networks

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Abstract— The purpose of this paper is to implement the theoretical closeness centrality measurement algorithm[1] that was proposed by the authors' research group in order to numerically analyze closeness centrality measures among workflow-performers on a workflow-supported social network model. We implement the essential part of the proposed algorithm[1], which is a closeness centrality analysis equation. Finally, we illustrate the implemented algorithm by showing its run-time screen-shots with an operational example.

Keywords— workflow-supported enterprise social network, workflow model, closeness centrality analysis, organizational knowledge discovery

I. INTRODUCTION

Recently, the workflow literature has been interested in quantitatively measuring the individuals' operational performances in workflow-supported enterprises. It starts from the strong belief that social relationships and collaborative behaviours among the individuals who are involved in enacting the specific workflow models affect the overall performance and being crowned with great successes in the real businesses and the working productivity as well. Accordingly, the authors' research group has been addressing the research and development issues of applying the concept of social network and its analysis methods to workflow-supported enterprises as a name of the workflow-supported enterprise social network[2].

As one of those research trials, we have been trying to develop several sophisticated and diversified analysis techniques, such as centrality[3-6], prestige, disconnectedness[7], correspondence[8,9], structural equivalence, and affiliation[10-16], to be applied to workflow-supported enterprise social networks. In particular, [1] was a typical trial formalizing a centrality analysis algorithm for measuring closeness centralities among workflow-performers affiliated in a workflow process model. Note that the centrality analysis used to be done by degree centrality, closeness centrality, betweenness centrality, or eigenvector centrality analysis techniques. The algorithmic formalism of closeness-centrality measurements is to quantitatively analyses the workflow-performers' intermediary capabilities in enacting a workflow procedure. Precisely, the eventual goal of

the algorithm was to measure and calculate theoretically the degree of work-intimacy among workflow-performers involved in a workflow model or a workflow package (a group of inter-relevant workflow models) on a workflow-supported enterprise or organization. In this paper, we implement the algorithm so as to be realized as a closeness centrality knowledge analyzer, and illustrate its run-time screen-shots with an operational example.

II. RELATED WORK

Recently, the workflow literature just starts being focused on social and collaborative work analysis on process-oriented organizations. Particularly, our work, workflow-supported social networking knowledge analysis, is directly related with a converged issue of social networks analysis issue and its visualization issue, which we need to dig into more specifically and profoundly as the future works of this research results. A typical one of a few research results on the social network analysis issue might be [17]. In this Ph.D. research, the thesis tried to build a fundamental theory of discovering organizational work-sharing networks, which would be a special type of social networks, from a specific workflow procedure. The organizational work-sharing networks discovered from the workflow procedure have been analyzed by a new statistical analysis approach. And [17] has also proposed a framework for discovering and analyzing workflow-supported social networks. However, the framework's analysis functionality supports only the degree centrality analysis capabilities, which is the simplest analysis techniques out of the four typical centrality analysis techniques, such as degree, closeness, betweenness, and eigenvector centrality measurements. Based upon the results of this paper, we have a plan to extend the framework by developing the closeness centrality analysis functionality in the near future.

III. THE THEORETICAL ALGORITHM FOR CLOSNESS CENTRALITY MEASUREMENTS

There exist several social network analysis techniques and algorithms for the centrality measures. Particularly among them, the most widely used centrality measures are degree, closeness, and betweenness, and these measures not only vary

in their applicability to nondirected and directed relations, but also differ at the individual actor and the group or complete network levels. As stated in the previous section, we are interested in quantitatively measuring the degree of closeness centrality of a workflow-supported social network by borrowing the well-known techniques[18] in the social network analysis literature. The analyzed measurements of closeness centrality reflect how near a performer is to the other performers in a workflow-supported social network. Ultimately, the implication of the algorithmic formalism to be deployed in this section aims to answer for the following question:

- How quickly can a performer interact with others in enacting the associated workflow procedure by communicating directly or through very few intermediaries?

A. Equations

Based upon the sociomatrix, $Z[N, N]$, we are able to calculate the closeness centrality measures by applying the equations given in [1]. That is, through the closeness centrality concept and its measurements we can obtain a reasonable level of analysis results, which is enough to answer to the issued question stated in the beginning of the section. The closeness centrality measures can be applied to the individual performer (*individual closeness centrality*) as well as the group of performers (*group closeness centrality*). An individual performer's closeness centrality is a function of its geodesic distance to all other performers. The geodesic distance implies the length of the shortest path connecting a dyad in a workflow-supported social network. The conceptual implication of the individual closeness centrality refers to how quickly a performer can interact with others by communicating directly or through very few intermediaries. Conclusively, for a binary nondirected workflow-supported social network with g performers, the index of individual closeness centrality[4] is computed as the inverse of the sum of the geodesic distances between performer i and the $(g - 1)$ other performers, where $d(N_i, N_j)$ represents the geodesic distance between two performers, i and j .

- The Index of Individual Closeness Centrality

$$C_c(N_i) = \frac{1}{\left[\sum_{j=1}^g d(N_i, N_j) \right]} (i \neq j) \quad (1)$$

- The Standardized Index of Individual Closeness

$$C_c^S(N_i) = \frac{C_c(N_i)}{g - 1} \quad (2)$$

B. Algorithm

In order to measure individual closeness centralities of workflow-supported enterprise social networks, Park et al. [1] proposed the individual closeness centrality analysis algorithm. As you see Figure 1, the algorithm takes as input a binary nondirected sociomatrix $Z[N, N]$, and the algorithm produces

a group of measurements of individual closeness centrality as the final output. The time complexity of the algorithm is $O(n^2)$ and the main algorithm named **iCcMeasurement()** procedure forms a typical double-loop construct with a recursive function, **iDistance()**, that can be computed in a constant time, $O(1)$, because the number of members of the set, D , ought to be much smaller than the number of individual performers. Consequently, by using the algorithm we are able to measure not only the standardized index of individual closeness centrality but also the group closeness centrality for a workflow-supported social network. Due to the page limitation, we won't describe the details of the remainder algorithms and their application examples to verify those algorithms.

The Individual Closeness Centrality Analysis Algorithm:

Global A Binary Nondirected SocioMatrix, $Z[N, N]$;

Global A Set of Individuals, C ;

Global A Set of Traversed Individuals, T ;

Global A Set of Direct-tied Individuals, D ;

Global A Set of Distance Values, $depth[N]$;

Procedure Name: iCcMeasurement

Input A Binary Nondirected SocioMatrix, $Z[N, N]$;

Output Individual Closeness Centralities, $C_c(o_1), \dots, C_c(o_n)$;

Local A Distance Matrix, $Depth[N, N]$;

Begin Procedure

For ($\forall o_i \in C$)

For ($\forall o_j \in C, o_i \neq o_j$)

$Depth(o_i, o_j) \leftarrow 1$;

Switch ($Z[o_i, o_j]$)

case 1: /* direct tie between o_i and o_j . */

$C_c(o_i) \leftarrow C_c(o_i) + Depth(o_i, o_j)$;

break;

case 0: /* no direct tie between o_i and o_j . */

Initialize

$(depth(o_1) \dots depth(o_n)) \leftarrow 1$;

$T \leftarrow o_i$;

$Depth(o_i, o_j) \leftarrow iDistance(o_i, o_j)$;

$C_c(o_i) \leftarrow C_c(o_i) + Depth(o_i, o_j)$;

break;

End

For

Return $\frac{1}{C_c(o_1)}, \dots, \frac{1}{C_c(o_n)}$;

End Procedure

Procedure Name: iDistance

Input The source individual, o_s , and the destination individual, o_d ;

Output The shortest distance between o_s and o_d ;

Begin Procedure

$D \leftarrow \emptyset$;

$T \leftarrow T \cup \{o_s\}$;

For ($\forall o_i \in C$)

If ($Z[o_s, o_i] = 1$) $D \leftarrow D \cup \{o_i\}$;

For;

For ($\forall o_i \in D$)

If ($Z[o_i, o_d] = 1$)

$depth(o_i) \leftarrow depth(o_i) + 1$;

Return $depth(o_i)$;

Fi;

For;

For ($\forall o_i \in D \wedge o_i \notin T$)

$depth(o_i) \leftarrow iDistance(o_i, o_d) + 1$;

$D \leftarrow D - \{o_i\}$;

For;

Return Minimum{ $depth(o_1), \dots, depth(o_m)$ };

/* m is the no. of members in D . */

End Procedure

Figure 1. Individual closeness centrality analysis algorithm

IV. IMPLEMENTING THE ALGORITHM

The author's research group implements a system that is able to explore, analyze, and visualize the planned workflow supported social networking knowledge discovered from a workflow model or a group of workflow models (or packages) formatted in XPDL[22]. In this section, we describe about the implementation details and its operational example of visualizing individual closeness centrality measurements.

A. System Architecture

Figure 2 shows the system architecture composed of the essential functional components coping with transformation phases and their relationships.

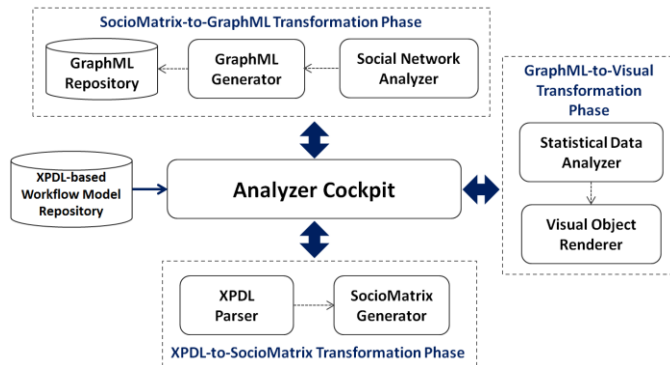


Figure 2. The system architecture of the analysis system

Through a graphical user interface (Analyzer Cockpit), system users can easily perform loading XPDL formatted files from a workflow model repository when the system is first started. The overall process of the system is divided into the three transformation phases as follows.

- **XPDL-to-SocioMatrix Transformation**
: Constructing a specific sociomatrix (directed/nondirected or binary/valued) from selected workflow models formatted in XPDL. Several social network analysis methods could be applied in the transformed sociomatrix as an analytical data structure to acquire desirable properties of the network.
- **SocioMatrix-to-GraphML Transformation**
: Generting a GraphML file from the sociomatrix through specific analysis phases. The generated GraphML[19] file embodies analysis results (measurements of individual closeness centrality in the case of this paper) as well as a graph representing structural properties of the workflow-supported enterprise social network.
- **GraphML-to-Visual Transformation**
: The generated GraphML file could be reused for visualizing the analysis results without repetitions of preprocessing and analysis phases. Each property embedded in the GraphML file is mapped to a visual object which augmented additional information and landscape options (shape, color, pattern, and size) chosen by a user. After final visualization step, the system observes and processes user interactions intended by the user to accomplish an objective.

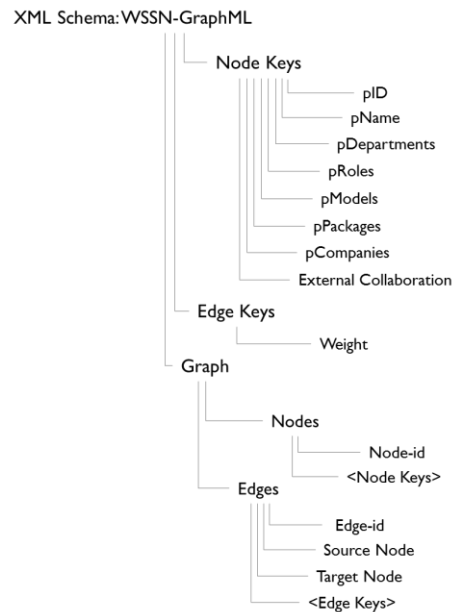


Figure 3. Fundamental GraphML schema for representing properties in workflow-supported enterprise social networks

The GraphML is an XML-based file format for representing graph data structures. The system exploits the GraphML to store intermediate results of preprocessing (XPDL-to-SocioMatrix transformation) and analysis (SocioMarix-to-GraphML transformation) phases and to reuse for directly visualizing analysis results without repetitions of phases previously performed. Therefore, the performance of the system will be higher through using the GraphML. The <Nodes> tag within the GraphML represents workflow-performers in the workflow-supported enterprise social network and the <Edges> tag contains relationships between workflow-performers. Figure 3 shows the fundamental GraphML schema for workflow-supported enterprise social networks. The schema can vary depending on the kind of analysis method which is applied to the respective execution by extending attributes in <Node Keys> tag or <Edge Keys> tag. For example, in the case of measuring closeness centrality, the attribute about the individual closeness centrality corresponding to each workflow-performer and the attribute about weight value between two workflow-performers can be added to <Node Keys> and <Edge Keys> respectively.

B. Operational Example

We define two workflow packages (HR-Dept-Workflow-Package1, and HR-Dept-Workflow-Package2) as an operational example to validate the system implemented by author's research group, and to show that the system can operates successfully in measuring and visualizing individual closeness centralities of workflow-supported enterprise social networks. The operational example, which describing the imaginary business processes for managing human resources in an organization, consists of 5 workflow model (Hiring Process,...,Salary Negotiation Process), 50 activities ($\alpha_1 \sim \alpha_{50}$), and 16 workflow-performers (Jeff,...,Holly).

Table 1. Details of the operational example

Workflow Package	Workflow Model	Workflow Activity	Workflow Performer
HR-Dept-Workflow-Package1	Hiring Process	$\alpha_1 \sim \alpha_{16}$ (16 activities)	Jeff Ed
	Performance Management Process	$\alpha_{17} \sim \alpha_{25}$ (9 activities)	Christiaan Emily Adam Cynthia
HR-Dept-Workflow-Package2	Employee Training Process	$\alpha_{26} \sim \alpha_{36}$ (11 activities)	Joylette Amanda Nathaniel
	Department Management Process	$\alpha_{37} \sim \alpha_{44}$ (8 activities)	Bryan Tamara Ashley
	Salary Negotiation Process	$\alpha_{45} \sim \alpha_{50}$ (6 activities)	Ryan Alan Chris Holly

Figure 4 and Figure 5 is to visualize the individual closeness centrality measurements of the workflow-performers within the operational example in forms of social graph and bar charts respectively. In Figure 4, the sizes of the circles imply the normalized values (between 0 and 1) of the closeness centrality of each workflow-performer, and the colors of the circles indicate the kind of department each workflow-performer works for—red circles (HR department), blue circles (accounting department), and green circles (management department) in the case of this paper.

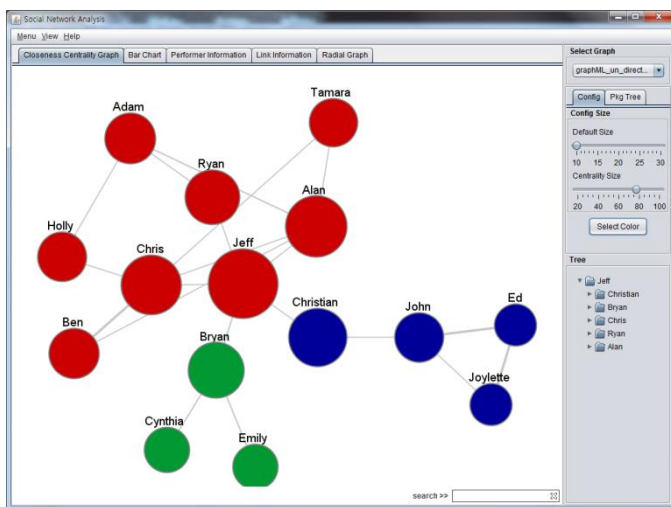


Figure 4. Visualization of the workflow-supported enterprise social network with closeness centrality measurements

Bar chart is a visual form which is especially useful on comparison and analysis of homogeneous values. From Figure 5, therefore, we can see that Jeff (the first bar on the left side in Figure 5) is the workflow-performer which scored highest value in measuring individual closeness centralities. In order to achieve these visualizations, the visual object renderer

component of the system uses JFreeChart[23] and Prepuse library[24].

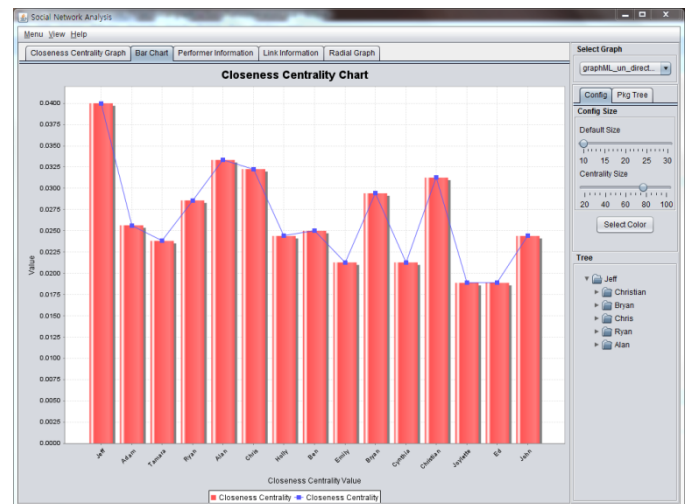


Figure 5. Bar charts representing individual closeness centrality measurements

V. CONCLUSION

The recent big-trends in working environments are undoubtedly large-scale workflow management systems with increasingly large and complex workflow applications. The large-scale workflow management systems ought to be reflecting the typical organization-wide perspectives like behavioural, social, informational, collaborative, and historical perspectives, and accordingly the visualization capability of the large-scale information ought to become a much more important feature in those large-scale systems. In this paper, we implement the algorithm so as to be realized as a closeness centrality knowledge analyzer, and illustrate its run-time screen-shots with an operational example.

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