Visual Analytics of Social Networks: Mining and Visualizing Co-authorship Networks

Carson Kai-Sang Leung, Christopher L. Carmichael, and Eu Wern Teh

The University of Manitoba, Winnipeg, MB, Canada
kleung@cs.umanitoba.ca

Abstract. Co-authorship networks are examples of social networks, in which researchers are linked by their joint publications. Like many other instances of social networks, co-authorship networks contain rich sets of valuable data. In this paper, we propose a visual analytic tool, called SocialVis, to analyze and visualize these networks. In particular, SocialVis first applies frequent pattern mining to discover implicit, previously unknown and potential useful social information such as teams of multiple frequently collaborating researchers, their composition, and their collaboration frequency. SocialVis then uses a visual representation to present the mined social information so as to help users get a better understanding of the networks.

Keywords: Human-computer interaction, data mining, frequent patterns, social network analysis and mining, social computing, social information, data visualization, information and knowledge visualization, visualizing social interaction, augmented cognition.

1 Introduction and Related Work

Over the past few years, the rapid growth and exponential use of social digital media has led to an increase in popularity of social networks and the emergence of social computing. In general, *social networks* [7,25] are structures made of social entities (e.g., individuals, corporations, collective social units, or organizations) that are linked by some specific types of interdependency (e.g., kinship, friendship, common interest, beliefs, or financial exchange). A social entity is connected to another entity as his next-of-kin, friend, collaborator, co-author, classmate, co-worker, team member, or business partner. *Social computing* [15,23,24] aims to computationally facilitate social studies and human-social dynamics in these networks as well as to design and use information and communication technologies for dealing with social context. It includes the development of human-computer interaction technologies for augmenting cognition [1,8]—i.e., naturally extending the minds of social entities so that they could effectively perform conscious mental activities such as solving problems, making decisions, acquiring new knowledge, and connecting with others—by social information and collective intelligence. Intuitively, *collective intelligence* [19] is a shared or group intelligence that emerges from the collaboration of some social entities. Joint publications are examples of solid outcomes of such collaboration.

D.D. Schmorrow and C.M. Fidopiastis (Eds.): FAC 2011, HCII 2011, LNAI 6780, pp. 335–345, 2011.

To facilitate augmented cognition, it is better to mine useful social information from the social networks.

Social network mining discovers implicit, previously unknown and potentially useful social information. Examples of mining tasks include predicting links [3], learning influence probabilities [9], and discovering suspicious groups [21]. In this paper, we apply another mining task to an important type of social networks. Specifically, we apply *frequent pattern mining* [13,14,18] (which was introduced [2] to analyze shopping market basket data for revealing shopper behaviour) to *co-authorship networks* for discovering important social information such as teams of frequently collaborating researchers, their composition, and their collaboration frequency. The mined information is helpful in applications like academic author ranking and expert recommendation. Related works on mining co-authorship networks mainly focused on different mining tasks (than finding frequent patterns about collaboration teams) such as classifying origins of researcher names [4] and analyzing supportiveness between pairs of researchers [11].

As "a picture is worth a thousand words", having a visual representation is generally more comprehensive to users than its textual representation. This explains why several visualizers have been proposed to visualize results (e.g., association rules [5], shopper patterns [6,16,17], clusters [20]) of various traditional data mining tasks. Similarly, while it is important to discover useful frequent social patterns from co-authorship networks, it is equally important to be able to visualize these patterns. Common visual representations of these networks include *node-link diagrams* [12], in which each node represents a social entity (researcher) and each edge connecting two nodes represents a linkage (co-authorship) between the two entities. This social information can also be represented in a *socio-matrix* (i.e., an adjacency matrix) [7]. However, node-link diagrams or socio-matrices do not necessarily capture frequency information associated with researchers and their co-authorship (e.g., number of papers authored by a researcher or the number of joint publications between two researchers). To capture multi-researcher co-authorship, one may use other representations such as *hypergraphs* [11] or *bipartite graphs* [22]. However, as frequency information is captured implicitly by these representations, users may encounter difficulties in counting frequency (due to overlapping clusters in hypergraphs or crossing-over lines in bipartite graphs). In this paper, we use an alternative representation in our proposed visual analytic tool called ***SocialVis***, which visualizes co-authorship networks so that it not only shows collaborators of user-selected researchers but also all the linkages among them. It clearly and explicitly presents frequency information for individual researchers and for pairs of researchers. Moreover, it shows the composition of teams of multiple researchers and their frequency information even for large co-authorship networks. Our ***key contribution*** of this invited paper is our proposal of SocialVis, which analyzes and visualizes social networks like co-authorship networks. SocialVis discovers useful social information and results of collective intelligence (e.g., publications) from the networks and allows users to visualize this information so that it helps them understand the networks and augment cognition. In general, SocialVis can serve as a standalone tool for mining and visualizing the networks and as a complement to existing tools (especially those that have features such as spotting and displaying interesting patterns but do *not* provide the frequency information of the patterns).

This paper is organized as follows. Next section discusses different visual representations of co-authorship networks. We propose our SocialVis in Section 3 and present evaluation results in Section 4. Conclusions are given in Section 5.

2 Representing Co-authorship Networks

Co-authorship networks are commonly represented as *node-link diagrams* [12], in which each node represents a researcher and each edge represents co-authorship between the two researchers. Fig. 1(a) presents a node-link diagram for a 1-degree egocentric network showing some selected collaborators of researcher Ng; Fig. 1(b) presents a node-link diagram for a 1.5-degree egocentric network, in which each dashed edge represents co-authorship between selected collaborators of Ng. (For simplicity of illustration, only some but not all collaborators of Ng are shown in the figures.) The social information depicted by the node-link diagram can be equivalently represented in a *socio-matrix* (i.e., an adjacency matrix) [7], in which every row and column is indexed by a researcher and each non-diagonal cell (*x,y*) keeps a Boolean value indicating the presence or absence of co-authorship between the two corresponding researchers *x* and *y*. See Fig. 1(c). However, node-link diagrams or socio-matrices do not necessarily capture quantitative information such as publication counts of researchers.

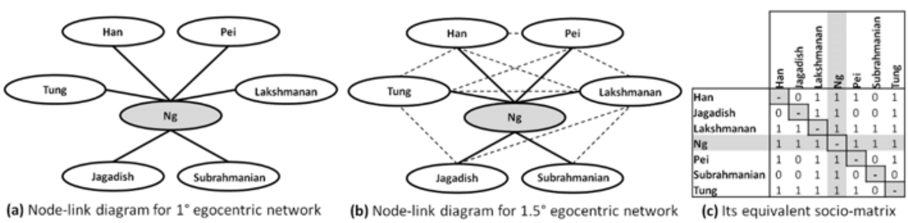

Fig. 1. Node-link diagrams & a socio-matrix

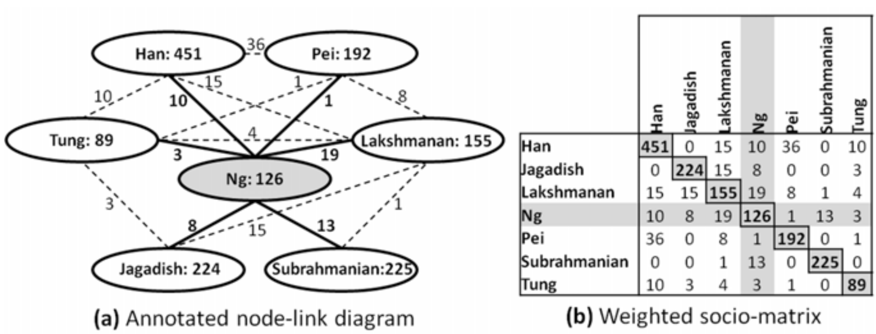

Fig. 2. An annotated node-link diagram & weighted socio-matrix for 1.5° egocentric network

To show quantitative information, one could use different node sizes and edge thickness in a node-link diagram. However, it is not easy to compare the size of two nodes or the thickness of two edges. Alternatively, one could annotate each node or edge with the quantitative information. Fig. 2(a) presents a node-link diagram for a 1.5-degree egocentric network showing some selected collaborators of researcher Ng, in which node *x* is annotated with the number of papers authored by researcher *x* and edge *xy* is annotated with the number of joint publications by researchers *x* & *y*. Similarly, one could replace the Boolean value in each non-diagonal cell (*x,y*) in a socio-matrix (indicating the presence or absence of some publications between the two researchers *x* & *y*) by an integer indicating the number of joint publications between *x* & *y*. The number of papers authored by a researcher could either (i) be augmented to the row or column label or (ii) be captured by the diagonal cell. See Fig. 2(b). While these representations show quantitative information for individual social entities and their pairwise relationships, they do not show the relationships among multiple social entities.

In many situations, relationships simultaneously involve more than two individuals in the network (e.g., papers co-authored by more than two researchers). For these situations, one could use (i) a *hypergraph* to group multiple researchers into the same cluster if they co-authored the same paper, (ii) a *dual hypergraph* to group multiple papers into the same cluster if they are co-authored by the same researcher, or (iii) a *bipartite graph* to link researchers to their corresponding joint publications. While the use of these three types of graphs depicts the composition of multi-entity relationships, these graphs do not clearly and explicitly provide users with frequency information. Moreover, multiple researchers may coauthor the same paper, and multiple papers may be coauthored by the same researcher. As such, clusters of entities (researchers) in hypergraphs often overlap with each other, and clusters of relationships (joint publications) in dual hypergraphs often overlap with each other. Linkages between researchers and papers in bipartite graphs often cross over each other. Hence, the use of these graphs can be quite unwieldy when depicting large social networks. An alternative visual representation is needed.

3 Analyzing and Visualizing Social Information with SocialVis

Given co-authorship network data (such as DBLP Bibliography records), our proposed visual analytic tool—called SocialVis—analyzes social networks and visualize social information. First, it applies frequent pattern mining algorithms [2,10] to find teams of frequently collaborating researchers and their collaboration frequency. Then, SocialVis represents the discovered frequent patterns in a two-dimensional space where the *x*-axis lists the researchers and the *y*-axis shows the number of their (solo or joint) publications.

To facilitate quick lookup researchers of user interest, SocialVis arranges researchers in *alphabetical order* on the *x*-axis. Besides this default ordering, SocialVis can also arrange researchers in *descending order of the number of their publications* (which gives users a quick insight about the frequency distribution of research publications because researchers with more publications appear on the left-hand-side and those with fewer publications appear on the right-hand-side).

Moreover, users do not need to select *all* researchers. Users can select one or more researchers based on their interest (e.g., select researcher Ng and some of his collaborators) for further analysis and visualization.

To clearly show the number of publications, SocialVis explicitly lists only the existing frequency values on the *y*-axis. This avoids large gaps between existing frequency values. Besides this default listing, SocialVis can also show the frequency values in linear scale, which allows users to get insight about the density or distributions of frequencies.

3.1 Visualizing Individual Researchers

When given a co-authorship network, a commonly asked question is as follow:

> **Q1.** How many papers published by this researcher?

The answer to Q1 may indicate how active this researcher is, which helps in ranking researchers in the network. To visualize the answer, SocialVis represents the number of papers authored by each individual researcher using a diamond-shaped icon ◀▶ (composed of a left-pointing triangle and a right-pointing triangle) in a two-dimensional space. The *x*-position of the icon indicates the researcher name, and the *y*-position of the icon indicates the number of his publications. See Fig. 3(a) for a screenshot of SocialVis, which explicitly shows the number of publications authored by each of the above seven selected researchers. From this figure, we can easily look up the number of Ng's publications (i.e., 126 papers). When researchers are arranged in descending order of the number of publications as shown in Fig. 3(b), we can easily observe that—among the seven selected researchers—Han published the most (with 451 papers) and followed by Subrahmanian (who published 225 papers).

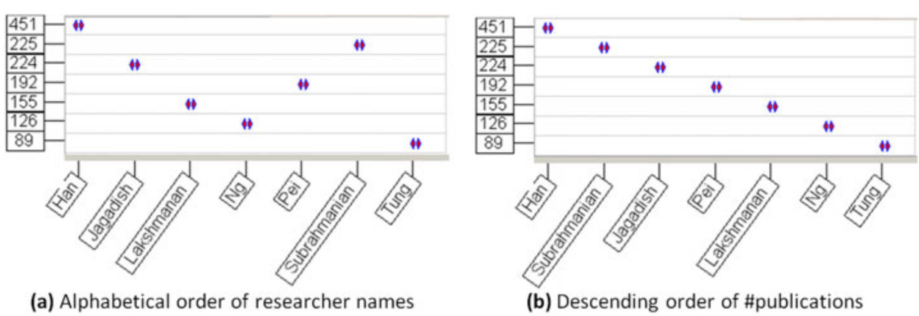

Fig. 3. SocialVis shows the numbers of papers authored by individual researchers

3.2 Visualizing Pairs of Researchers

Besides Q1, the following is the next commonly asked questions:

> **Q2.** Did this researcher collaborate with another researcher? If so, how many papers co-authored by them?

Answers to Q2 help users understand pairwise connections—in the form of joint publications—between pairs of researchers. SocialVis represents each pairwise connection using a horizontal line linking the left-pointing and right-pointing triangles (representing the two researchers) in the form of a bi-direction arrow ◀—▶. The use of horizontal lines avoids crossing over of lines (as in bipartite graphs). The *y*-position of the line explicitly indicates the number of co-authored papers. For example, Fig. 4(a) shows that Han & Pei co-authored 36 papers. It also shows that Han co-authored 10 papers with Ng and 10 papers with Tung.

When combined with the information depicted by Fig. 3, we can infer that, among 451 papers published by Han, 10 of them were co-authored with Ng (which means the remaining 451–10 = 441 papers were either solo publications of Han or the results of his other collaboration in which Ng did not participate).

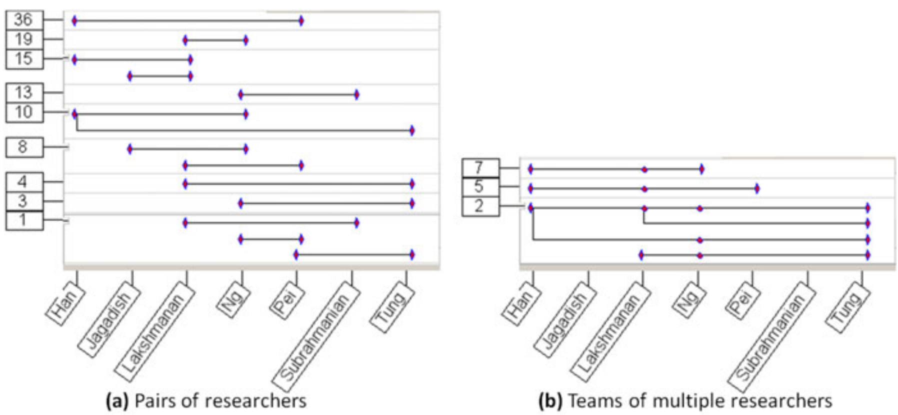

Fig. 4. SocialVis shows the numbers of papers co-authored by pairs or teams of researchers

3.3 Visualizing Collaborating Researchers in Teams

With the above two features of SocialVis (Sections 3.1 & 3.2), we can visualize the publication counts of each individual researcher and pair of researchers. For instance, we observed from Fig. 4(a) that there are pairwise connections between Han, Lakshmanan and Ng (e.g., Lakshmanan & Ng co-authored 19 papers, Han & Lakshmanan co-authored 15 papers, and Han & Ng co-authored 10 papers), from which we can infer that they together co-authored at most 10 papers (i.e., an *upper bound* for the number of their joint publications). Since we cannot infer the *exact* number of joint publications, it is unclear whether or not these three researchers collaborated together in a team. Hence, a logical question is:

> **Q3.** Did these k researchers (where $k \geq 3$) collaborate in a team? If so, exactly how many joint papers co-authored by them?

Answers to Q3 help users understand social linkage not only between two researchers but among multiple researchers. SocialVis uses a horizontal line to connect two triangles and k–2 circles representing all k researchers in a team (e.g., ◀–●–●–▶ represents a team of 4 researchers). The *y*-position of the line explicitly indicates the number of their joint publications. For example, Fig. 4(b) clearly shows that Han, Lakshmanan & Ng together co-authored 7 papers (cf. the upper bound of 10 papers inferred without using this feature of visualizing multi-researcher teams). As Ng participated in only 7 of 15 papers co-authored by Han & Lakshmanan, the remaining 15–7 = 8 papers were either written only by both Han & Lakshmanan or written together with their other collaborators.

Fig. 4(b) also shows that Han, Lakshmanan, Ng & Tung together co-authored 2 papers. This means that, among the 7 papers co-authored by the first three researchers, Tung co-authored only 2 of them, but he did not participate in the other 5 publications. Moreover, observing that the number of joint publications for Han, Lakshmanan & Tung is also 2, we can conclude that Ng participated in *all* the 2 papers jointly written by Han, Lakshmanan & Tung.

When combining the information depicted by Fig. 4(b) with that by Fig. 4(a), we make the following interesting observation: Although Han, Ng & Pei collaborated in pairs (with Han & Pei co-authored 36 papers, Han & Ng co-authored 10 papers, and Ng & Pei co-authored 1 paper), they did not write a joint paper together as indicated by the absence of any horizontal line connecting all three of them. This is different from the aforementioned ⟨Han, Lakshmanan, Ng⟩ team, in which the three researchers collaborated in pairs and all together.

Based on the numbers of joint publications of the ⟨Han, Lakshmanan⟩ and ⟨Han, Lakshmanan, Ng⟩ teams shown in Fig. 4, we conclude that Ng participated in only 7 out of the 15 papers co-authored by both Han & Lakshmanan. Furthermore, when observing the number of papers authored by Han is 451, we conclude Lakshmanan & Ng participated in only 7 out of these 451 papers (which implies that the remaining 451–7 = 444 papers were either solo publications of Han or the results of his other collaboration in which Lakshmanan & Ng did not participate together).

3.4 Visualizing the Entire or Partial Collaborating Teams

Based on the above observations, users can visualize the frequency information for teams of k researchers (for any $k \geq 1$) using the above three features of SocialVis (Sections 3.1-3.3). For example, users can conclude that Lakshmanan & Ng participated in 7 out of the 451 papers published by Han, but they may have difficulties in determining how many of the remaining 444 papers were written solely by Han and how many involved other collaborator. So, the following question is not uncommon:

> **Q4.** Did we have the complete list of co-authors for this paper? If so, how many co-authors are there? How many papers were jointly co-authored by all and only those researchers in this team?

Answers to Q4 help users understand (i) whether they found the *entire* frequently collaborating team or just a subset of it, (ii) the composition of the entire team, and (iii) the collaboration frequency of the entire team. To distinguish a complete team from a partial team, SocialVis replaces the right-pointing triangle with a bar ▌ for the complete team. See Fig. 5(a), which shows that Han is a sole author of 32 publications and Ng & Subrahmanian jointly published 8 papers (without any other co-authors). The figure also shows that the ⟨Han, Lakshmanan, Ng, Tung⟩ team co-authored 2 papers and its subset—the ⟨Han, Lakshmanan⟩ team—co-authored another 2 papers.

When we combine all the information depicted by Figs. 3-5, we get a better understanding of the networks. Recall from Section 3.2, we knew that Ng participated in 10 of 451 Han's papers, but we were uncertain about the remaining 441 papers. Now, with Fig. 5(a), we know Han wrote 32 papers alone, which means he co-authored the remaining 441–32 = 409 papers with researchers other than Ng. Fig. 5(a) also clears up the uncertainty in Section 3.3: (i) Among the 8 papers co-authored by Han & Lakshmanan but not Ng, 2 were written only by both Han & Lakshmanan (which means the remaining 6 were with Han & Lakshmanan's other collaborators besides Ng). (ii) Among the 444 Han's papers not co-authored with both Lakshmanan & Ng, 32 were solo publications of Han (which means the remaining 412 were the results of his other collaboration in which Lakshmanan & Ng did not participate together).

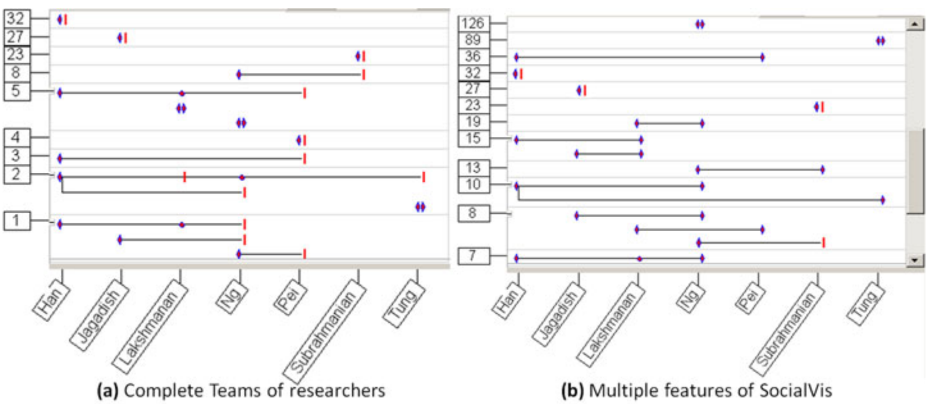

Fig. 5. SocialVis shows entire teams of researchers and their publication counts

3.5 Visualizing Large Co-authorship Networks

For clarity of our illustration, we only show features of SocialVis one at a time in each of the above figures (e.g., teams of multiple researchers in Fig. 4(b)). In general, users could select one or more features so that SocialVis displays the corresponding results on the same screen. See Fig. 5(b).

To visualize large co-authorship networks, SocialVis gives users an overview of all social information mined from the networks. To avoid over-crowdedness, SocialVis only displays some labels on the axes. As researcher names are (by default) arranged in alphabetical order on the *x*-axis, users can easily determine the hidden names. Moreover, SocialVis provides users with interactive features for selection/filtering so that they can focus on the area of user interest (e.g., some specific researchers and/or collaboration frequencies). Users can then zoom into, or out of, that area. SocialVis also provides users with scrollbars on both *x*- and *y*-directions so that users can easily scroll & explore different areas of the mined results and effectively access the useful social information about the networks.

4 Evaluation

To assess the effectiveness of SocialVis (our visual analytic tool) in conveying important social relationships (e.g., co-authorship information) and their frequency information mined from the social networks, we conducted a user evaluation. The evaluation was primarily case-based, within which users were required to answer different questions based on the information depicted by SocialVis. Sample questions include the following: How many papers are co-authored by Ng? Among them, how many were his sole publication? Did Ng collaborate with Han & Lakshmanan together? What is the number of their joint publications?

We recruited 18 participants, and none of them was exposed to our proposed SocialVis before. We began the evaluation by presenting our SocialVis and asking them to explore it at their own will. We did not give them any information regarding what the icons and representations meant in the visualization. We first questioned them on what they were able to identify. Due to our intuitive representation, the results showed that 78% of the participants were able to identify the basic meaning behind the representations (e.g., teams of *k* researchers and numbers of their joint publications). Only 22% of the participants had slight problems in distinguishing entire teams from partial teams. Afterwards, we gave the participants information on how to read the graphs (especially, the differences between right-pointing triangles and bars). Then, all participants were able to correctly answer all the given questions.

Moreover, these participants were asked to answer the same set of questions using other graphical representations of the network such as annotated node-link diagrams, weighted socio-matrices, hypergraphs, dual hypergraphs, and bipartite graphs. As expected, participants were only able to answer questions about individual or pairs of researchers but not teams of multiple researchers using the first two types of graphs. Most participants found it difficult to answer questions about multi-researcher teams using the latter three types of graphs as answers were not explicitly shown as by SocialVis. Participants need to manually dig out the information from overlapping clusters (in hypergraphs or dual hypergraphs) or crossing-over lines (in bipartite graphs) and to carefully count the numbers. As SocialVis clearly and explicitly provides the frequency information, participants can easier read this information.

5 Conclusions

A co-authorship network is one type of social networks, in which researchers are connected by their joint publications. In this paper, we proposed SocialVis to analyze and visualize these networks. Specifically, it applies frequent pattern mining to find useful social information such as the entire or partial teams of *k* frequently collaborating researchers and numbers of their joint or solo publications. It also presents these mining results graphically to users so that they can easily visualize the valuable social information about outcomes of collective intelligence and get a good understanding of the networks, which in turn helps users augment cognition. In general, SocialVis can serve either as a standalone visual analytic tool for revealing interesting social relationships among multiple entities in the networks or as a complement to existing visualizers by providing users with additional quantitative information such as publication counts. As ongoing work, we are extending SocialVis to analysis and visualize higher dimensional relationships such as where (venue) did the research papers published and/or when (year) did they published.

Acknowledgments. This project is partially supported by Natural Sciences and Engineering Research Council of Canada (NSERC) in the form of research grants.

References

1. Adams, R., Gill, S.P.: Augmented cognition, universal access and social intelligence in the information society. In: Schmorrow, D.D., Reeves, L.M. (eds.) FAC 2007, HCII 2007. LNCS (LNAI), vol. 4565, pp. 231–240. Springer, Heidelberg (2007)
2. Agrawal, R., Imielinski, T., Swami, A.N.: Mining association rules between sets of items in large databases. In: ACM SIGMOD 1993, pp. 207–216 (1993)
3. Benchettara, N., Kanawati, R., Rouveirol, C.: Supervised machine learning applied to link prediction in bipartite social networks. In: ASONAM 2010, pp. 326–330 (2010)
4. Biryukov, M.: Co-author network analysis in DBLP: classifying personal names. In: MCO 2008. CCIS, vol. 14, pp. 399–408. Springer, Heidelberg (2008)
5. Blanchard, J., Guillet, F., Briand, H.: Interactive visual exploration of association rules with rule-focusing methodology. KAIS 13(1), 43–75 (2007)
6. Carmichael, C.L., Leung, C.K.-S.: CloseViz: visualizing useful patterns. In: ACM UP 2010, pp. 17–26 (2010)
7. Carrington, P.J., Scott, J., Wasserman, S. (eds.): Models and Methods in Social Network Analysis. Cambridge University Press, Cambridge (2005)
8. Chi, E.H.: Augmented social cognition: using social web technology to enhance the ability of groups to remember, think, and reason. In: ACM SIGMOD 2009, pp. 973–984 (2009)
9. Goyal, A., Bonchi, F., Lakshmanan, L.V.S.: Learning influence probabilities in social networks. In: ACM WSDM 2010, pp. 241–250 (2010)
10. Han, J., Pei, J., Yin, Y., Mao, R.: Mining frequent patterns without candidate generation: a frequent-pattern tree approach. Data Mining and Knowledge Discovery 8(1), 53–87 (2004)
11. Han, Y., Zhou, B., Pei, J., Jia, Y.: Understanding importance of collaborations in co-authorship networks: a supportiveness analysis approach. In: SDM 2009, pp. 1111-1122 (2009)
12. Hansen, D.L., Shneiderman, B., Smith, M.A.: Analyzing Social Media Networks with NodeXL. Morgan Kaufmann, Burlington, MA (2011)
13. Lakshmanan, L.V.S., Leung, C.K.-S., Ng, R.T.: Efficient dynamic mining of constrained frequent sets. ACM TODS 28(4), 337–389 (2003)
14. Leung, C.K.-S., Carmichael, C.L.: FpVAT: a visual analytic tool for supporting frequent pattern mining. SIGKDD Explorations 11(2), 39–48 (2009)
15. Leung, C.K.-S., Carmichael, C.L.: Exploring social networks: a frequent pattern visualization approach. In: IEEE SocialCom 2010, pp. 419–424 (2010)

16. Leung, C.K.-S., Irani, P.P., Carmichael, C.L.: FIsViz: a frequent itemset visualizer. In: Washio, T., Suzuki, E., Ting, K.M., Inokuchi, A. (eds.) PAKDD 2008. LNCS (LNAI), vol. 5012, pp. 644–652. Springer, Heidelberg (2008)
17. Leung, C.K.-S., Irani, P.P., Carmichael, C.L.: WiFIsViz: effective visualization of frequent itemsets. In: IEEE ICDM 2008, pp. 875–880 (2008)
18. Leung, C.K.-S., Khan, Q.I., Li, Z., Hoque, T.: CanTree: a canonical-order tree for incremental frequent-pattern mining. KAIS 11(3), 287–311 (2007)
19. Lévy, P.: Toward a self-referential collective intelligence some philosophical background of the IEML research program. In: Nguyen, N.T., Kowalczyk, R., Chen, S.-M. (eds.) ICCCI 2009. LNCS (LNAI), vol. 5796, pp. 22–35. Springer, Heidelberg (2009)
20. Makanju, A., Brooks, S., Zincir-Heywood, A.N., Milios, E.E.: LogView: visualizing event log clusters. In: PST 2008, pp. 99–108 (2008)
21. Milani Fard, A., Ester, M.: Collaborative mining in multiple social networks data for criminal group discovery. In: IEEE SocialCom 2009, pp. 582–587 (2009)
22. Misue, K.: Visual analysis tool for bipartite networks. In: Lovrek, I., Howlett, R.J., Jain, L.C. (eds.) KES 2008, Part II. LNCS (LNAI), vol. 5178, pp. 871–878. Springer, Heidelberg (2008)
23. Ugai, T., Aoyama, K.: Organization diagnosis tools based on social network analysis. In: Smith, M.J., Salvendy, G. (eds.) Human Interface 2009, Part I, HCII 2009. LNCS, vol. 5617, pp. 181–189. Springer, Heidelberg (2009)
24. van Ham, F., Schulz, H.-J., DiMicco, J.M.: Honeycomb: visual analysis of large scale social networks. In: Gross, T., Gulliksen, J., Kotzé, P., Oestreicher, L., Palanque, P., Prates, R.O., Winckler, M. (eds.) INTERACT 2009, Part II . LNCS, vol. 5727, pp. 429–442. Springer, Heidelberg (2009)
25. Wasserman, S., Faust, K.: Social Network Analysis: Methods and Applications. Cambridge University Press, Cambridge (1994)