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A Complex Network Analysis of the Weighted Graph of the Web2.0 Service Network

Kibae Kim, Jörn Altmann

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공 과 대 학, 기술경영경제정책 대학원과정
151-742 서울시 관악구 관악로 599

Technology Management, Economics, and Policy Program
College of Engineering, Seoul National University
599 Gwanak-Ro, Gwanak-Gu, Seoul 151-742, South-Korea
Phone: ++82-2-880-9140, Fax: ++82-2-880-8389

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Jörn Altmann, Editor

Office: 37-305
Technology Management, Economics, and Policy Program
College of Engineering
Seoul National University
599 Gwanak-Ro, Gwanak-Gu
Seoul 151-742
South-Korea

Phone: +82-70-7678-6676
Fax: +1-501-641-5384
E-mail: jorn.altmann@acm.org

A Complex Network Analysis of the Weighted Graph of the Web2.0 Service Network

Kibae Kim[1], Jörn Altmann[2]

[1] Institut für Datentechnik und Kommunikationsnetze
Technische Universität Braunschweig
Hans-Sommer-Str. 66, 38106 Braunschweig, Germany
kim@ida.ing.tu-bs.de

[2] Department of Industrial Engineering
College of Engineering
Seoul National University
Seoul, South-Korea
jorn.altmann@acm.org, junhwang@snu.ac.kr

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Abstract: Service providers that own Web2.0 services allow Internet users not only to access their Web2.0 services but also to create new Web2.0 services (mashups) based on theirs. This creation of mashups generates the Web2.0 service network, in which a node represents a Web2.0 service and a link between two nodes represents a mashup using the two Web2.0 services linked. Since this Web2.0 service network is constructed without the control of a single entity (i.e., it is self-organizing), the network topology of the Web2.0 service network shows the scale-free characteristic. With respect of the weighting of those links, however, there are different approaches. Prior research either considered binary links or links that are weighted by summing up the number of mashups. Since the last approach might overestimate the strength of the link, we calculate the link weights according to Newman's approach in this paper. Based on this weighted graph of the Web2.0 service network, we investigate the topology of the weighted graph and examine the pattern of Web2.0 service creations. Our results show that the Newman-based weighted graph of the Web2.0 service network shows the characteristics of a scale-free network and a small-world network.

Keywords: Web2.0 services, mashup, network topology analysis, self-organized networks, small-world networks, scale-free networks, complex networks.

JEL Classification Numbers: C02, C63, D80, D85, L86, O31.

1. Introduction

Many Web2.0 service providers allow free access to their Web2.0 services through open Application Programming Interfaces (API). An Internet user (in the role of a Web2.0 service developer), who is able to apply Web2.0 technologies (e.g., Asynchronous JavaScript and XML), can combine these Web2.0 services to develop new ones [1] [2]. These new Web2.0 services, which are called Web2.0 mashups, or simply mashups [3] [4] [5], might also include the Internet user's own data and functions.

To analyze the creation of Web2.0 services, we introduce the Web2.0 service network. A node of the Web2.0 service network represents an existing Web2.0 service and a link between two nodes represents the existence of a mashup using these two Web2.0 services.

Since the Web2.0 service network is based on user decisions, we expect the Web2.0 service network to be self-organized. In particular, we expect the Web2.0 service network to show features that appear in complex social networks (e.g., random networks, small world networks, and scale-free networks).

For about a decade, prior research has examined mechanisms for generating network topologies that are similar to those of self-organized social networks. Watts and Strogatz showed that the random rewiring model can transform a regular network into a small-world network by randomly rewiring links of the regular network [6]. In small world networks generated by Watts and Strogatz, a node is embedded in a small, cohesive cluster that can reach any other node in the network through a very few intermediaries only.

Furthermore, empirical studies of the WWW, open source social networks, and academic collaboration networks suggest that a majority of self-organized networks are scale-free. Under this property, the degree frequency decays following a power function [8] [9] [10] [11] [12]. The nodes that are located in the long tail of the power function are called hubs. They make the network diameter small [7].

It is important to analyze the characteristics of these self-organized networks, since the characteristics affect the performance of communication within the network and the robustness of the network.

With respect to information diffusion in networks, the average shortest path is important. Information diffuses quickly, if the information initiates at a hub within a scale-free network [14] [15].

Links within a scale-free network are concentrated on a few hubs while links are equally distributed among all nodes in small world and random networks. Therefore, scale-free networks are not robust to intentional attacks comparing to random networks [16]. On the other hand, due to the same reason, scale-free networks are stronger to random failures than random networks.

Several studies examined the topology of networks related to Web2.0 services. Fu et al. analyzed the network topology of social networking services. Hwang et al. examined the Web2.0 service network to show its scale-free property [17] [18]. Kim et al. investigated the openness between subgroups, showing that openness impacts the evolution of complex network and, in particular, Web2.0 service networks [19].

However, these studies do not consider the weights of the Web2.0 service network comprehensively. Although Hwang et al. (2009) and Kim et al. (2010) considered weights in the Web2.0 service network, the calculation of a weight of a link is the simple summation of the number of mashups [18] [19]. This calculation of weights may overestimate the strength of a link between two nodes. For example, consider a mashup *i* that is created with two Web2.0 services (i.e., *x* and *y*) and a mashup *j* that is created with three Web2.0 services (i.e., *x*, *y*, and *z*). The contribution of each of the two Web2.0 services *x* and *y* to mashup *i* is larger than the contribution of each of the three Web2.0 services *x*, *y*, and *z* to mashup *j*. Therefore, the link through mashup *j* should be weighted less than the link through mashup *i*. In order to account for this, we follow Newman's approach. Newman calculated the weight of a link in an academic collaboration network as the sum of all collaboration divided by the total number of co-authors minus one [10], avoiding overestimation.

In this paper, we investigate the topology of the Web2.0 service network that has been established according to Newman's approach [10]. In our analysis, we check whether the pattern of the mashup creation corresponds to that of well-known self-organized networks. In particular, we examine whether the Web2.0 service network shows small-world network and scale-free network properties. Finally, we compare the result with previous research on Web2.0 service network.

The remainder of this paper is organized in 3 sections. The next section introduces the literature on node degree distributions, small-world networks, scale-free networks, and on weighted graphs. In section 3, the Web2.0 service network is analyzed with respect to indicators of small-world networks and scale-free networks. In section 4, we conclude the paper with a discussion on the mashup creation within the Web2.0 service network.

2. Theoretical Background on Complex Networks

2.1. Classification of Node Degree Distributions

The topologies of networks can be classified into two groups according to the type of heterogeneity of node degree distributions. The first group comprises networks, which node degree distribution varies around a mean value (i.e., homogeneous node degree distribution). Examples of those networks are regular networks, small-world networks, and random networks (e.g., Poison distributed random network) [6]. These networks have no node with a distinctive central position. All nodes have a node degree that is in a range around the mean value of the node degree in the network. The only difference between these three networks is that the topology of a small-world network shows a higher variance around the mean value (i.e., more randomness) than the topology of a regular network, and the topology of a random network shows a higher variance around the mean value (i.e., more randomness) than the topology of a small-world network.

The second group of networks is identified through a node degree distribution that does not vary around the node degree mean value. These networks are identified through the existence of distinctive central nodes, which are connected to many nodes, through many nodes with only one neighbor, and through the lack of nodes with more than one common neighbor (i.e., heterogeneous node degree distribution). Examples of this group are scale-free networks [16] [22] and tree-structured networks. A tree network has a heterogeneous node degree distribution, since a central node stretches to terminal nodes through a few intermediary nodes. A star network is a tree network where all nodes have exactly one link except for one node that connects all other nodes.

2.2. Small-World Networks

Watts and Strogatz generated a small-world network by rewiring links of a regular network with probability p [6]. They used the average clustering coefficient to measure how the network is clustered, and the average shortest path length to evaluate how near the members in the network are.

The clustering coefficient $Cl_v(g)$ of node v in graph g is defined as the ratio of the number of links between neighbors of node v, to the theoretically maximum number of links between them:

$$Cl_v(g) = \frac{\sum_{i,j \in N_v(g)} a_{ij}}{k_v(k_v - 1)/2} \qquad (1)$$

where a_{ij} is an element of adjacency matrix A. a_{ij} is 1 if node i is connected with node j, otherwise 0. $N_v(g)$ denotes the set of neighbors of node v. k_v represents the degree of node v (i.e., the number of links of node v), which is calculated as

$$k_i = \sum_j a_{ij} \qquad (2)$$

The average clustering coefficient is calculated as the average of the clustering coefficient of all nodes v.

The shortest path length $d(i,j)$ between node i and node j is defined as the number of links in the shortest path. The average shortest path is defined as the average of the shortest paths between any two nodes i and j.

Regular networks have the same number of links per node. Consequently, the degree distribution shows a peak at a certain degree. In this kind of network, each node is embedded in a cluster (i.e., high average clustering coefficient) but is far from other nodes (i.e., long average shortest path length). If the rewiring probability (i.e., the probability that a link is chosen to be rewired) goes to 1 (i.e., all links in the regular network are rearranged), the network transforms to a Poisson distributed random network. In this random network, nodes rarely share neighbors (i.e., low average clustering coefficient) and are close to each other (i.e., short average shortest path length).

The small-world network is positioned between the Poisson distributed random network and the regular network. It is highly clustered (i.e., high average clustering coefficient) and has nodes that are connected closely (i.e., short average shortest path length) [6]. It implies that the nodes in the small-world network are connected to each other efficiently. It was empirically tested by Milgram that a real world social network has a small world-network topology [20]. The small-world topology implies that a person frequently meets a friend of his friends.

2.3. Scale-Free Networks

Empirical studies of the WWW, open source social networks, and academic collaboration networks suggest that a substantial number of self-organized networks are scale-free [8] [9] [10] [11] [12]. Scale-free networks are networks, whose frequency $P(k)$ of node degree k decays by a power function $k^{-\gamma}$. Prior research explained that a scale-free network is generated by a simple rule such as the preferential attachment rule or the rule of merging and regeneration [22] [23] [24].

Generally, noise appears in the high node degree range, which represents important information about a scale-free network, due to the low frequency in this range. In order to eliminate the problem of low frequency, the cumulative degree distribution is more useful. It determines the scale-free characteristic of a network by calculating $k_>$, i.e., the frequency of node degrees larger than k [21]:

$$P(k_>) = \int_k^\infty P(k)dk \sim k^{-(\gamma-1)} . \qquad (3)$$

The distribution of a scale-free network is heterogeneous, compared to the distributions of Poisson distributed random networks and small world networks. It implies that a few hubs have a large number of links and a large part of nodes has only a small number of links [7] [8].

2.4. Weighted Graphs

So far, existing literature showed only the previously mentioned properties of binary networks. In those binary networks, the element a_{ij} of an adjacency matrix A indicates only the presence of a link between node i and j (i.e., the neighborhood of a node). Although the weight of a link also exhibits important information about networks, it has not been considered until now. In particular, the weights show how frequently the nodes interact with each other.

The weights can be defined in different ways, mainly depending on the context of the network analysis. For example, the weight of a link between two adjacent routers in the Internet can be defined as the data traffic capacity between them. The degree of intimacy, or goodwill, between two friends is also a good example for expressing it with a link weight.

Newman suggested a measure for capturing the strength of collaboration between two coauthors of an academic article [25]. He assumed that the strength of collaboration between two authors is proportional to the number of articles collaborated on, and that it is inversely proportional to the number of authors participating in the article. Under this assumption the weight w_{ij} of a link between author i and author j in an academic collaboration network is defined as:

$$w_{ij} = \sum_p \frac{\delta_i^p \delta_j^p}{n_p - 1} \qquad (4)$$

δ_i^p represents the contribution of author i to paper p. δ_i^p is 1 if author i contributed to paper p, otherwise 0. n_p is the number of authors who contributed to paper p.

With the weights between node i and node j defined, the complex network indicators for weighted graphs can be defined corresponding to the indicators for binary networks. The strength of the degree of node i in weighted networks is defined (analogous to the node degree in a binary graph) as the sum of link weights that node i involves [25] [26] [27]:

$$s_i = \sum_j w_{ij} \qquad (5)$$

Furthermore, the definitions of path length and clustering coefficient need to be adapted. For the weighted shortest path length, $d^w(i,j)$ between node i and node j is defined as the minimum sum of inversed weights of the links on the path between node i and node j [26]:

$$d^w(i,j) = \min\left(\frac{1}{w_{ih}} + \cdots + \frac{1}{w_{gj}}\right) \qquad (6)$$

If each weight goes to 1, or if each weight implies only the presence of a link, the equation of the weighted shortest path length $d^w(i,j)$ is reduced to that of a binary graph.

With respect to the clustering coefficient, it is assumed that a node is clustered more cohesively with its neighbors if its link weights are greater than 1. The definition of the clustering coefficient Cl_v of node v has been extended by Barrat et al. (2004) to capture this assumption [27]. We corrected their definition by multiplying it with a factor 2, in order to get $0 \leq Cl_v^w \leq 1$:

$$Cl_v^w = \frac{2}{s_v(k_v - 1)} \sum_{i,j} \frac{(w_{vi} + w_{vj})}{2} a_{vi} a_{vj} a_{ij} \qquad (7)$$

Here, each triplet ($a_{vi}\, a_{vj}\, a_{ij}$) is weighted with the average link weight obtained from the two links from node v to the two neighboring nodes i and j. This sum of the weighted triplets is normalized by $s_v(k_v\text{-}1)/2$, considering the strength of the degree of node v.

3. Analysis

3.1. Description of Data

A list of Web2.0 services and mashups has been gathered from the Website www.programmableweb.com. It includes 445 Web2.0 services with open APIs and 1,929 Web2.0 mashups. These services have registered with the Website between September 1, 2005 and May 21, 2007. From this initial data set, 214 Web2.0 services were deleted in the data set, since they were not used to develop any Web2.0 mashup during the study period. Furthermore, we eliminated 15 Web2.0 services since they were solely used for mashup creation (i.e., each of these Web2.0 services was not used together with any other Web2.0 service for creating a mashup. The deletion of these Web2.0 services does not affect the network characteristic, since these Web2.0 services are isolated in the Web2.0 service network. Consequently, the number of Web2.0 actually used for the analysis is 216.

The Web2.0 service network was constructed as described earlier. A node of the Web2.0 service network represents an existing Web2.0 service and a link between two nodes indicates which two Web2.0 services were jointly used to create a new Web2.0 mashup.

Therefore, an element a_{ij} of the adjacency matrix A of the Web2.0 service network is 1, if the two Web2.0 services were used at least once to create a Web2.0 mashup. Otherwise, a_{ij} is equal to 0. Within the generated Web2.0 service network, 1929 Web2.0 mashups generated 1916 links. The average degree of a node is $k = 8.870$.

The weights of the Web2.0 service network were calculated following Newman's approach [10]. In equation 6, it was assumed that δ_i^p is 1, if Web2.0 service i was used to create mashup p, otherwise 0. As a result, the total weight calculated is 924.738 for the 1916 links in the Web2.0 service network.

3.2. Properties of Weights

The distribution of the link weights of the Web2.0 service network shows a power law distribution. The logarithm of the cumulative number of weights decays linearly according to the logarithm of the weight (Fig. 1a). The result of the linear regression on this data shows that the slope is 1.945, the significance probability is 0.000 and the determination coefficient R^2 is 0.974. That means, the distribution function of the weight w is $P(w) \sim w^{-2.945}$, and the relationship is statistically significant

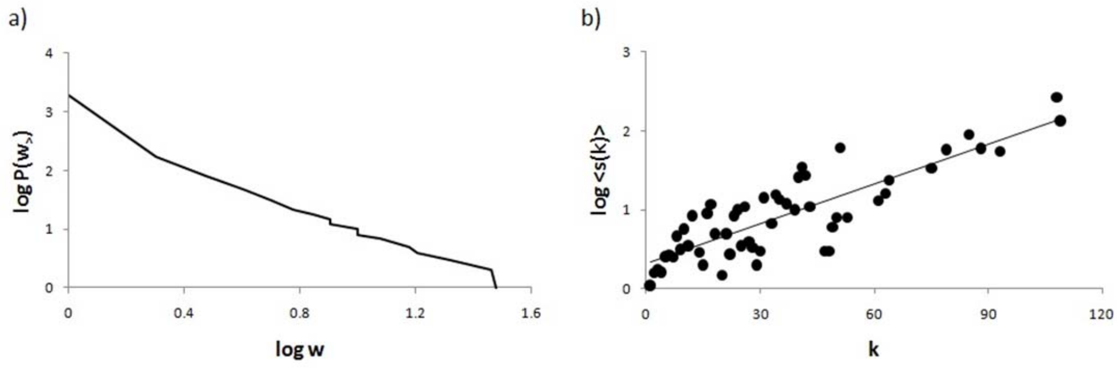

Figure 1. Properties of the weights of the Web2.0 service network: a) the weight distribution in the log-log scale; and b) the relationship between the node degree k and the logarithm of the strength of the node degree.

The strength s of a node tends to increase exponentially as the node degree k of the node increases. The logarithm of the strength $s(k)$ conditional on k shows a slightly positive linear correlation with k (Fig. 1b). The slope in the log-linear regression model is 0.013. The significance probability is 0.000 and the determination coefficient R^2 is equal to 0.450. These results exhibit that Web2.0 services, which have been combined with many different Web2.0 services, are utilized more frequently to develop mashups.

3.3. Small-World Properties

To evaluate the small-world property of the weighted graph of the Web2.0 service network, we measure the weighted clustering coefficients and the average weighted shortest path length of the network. The average weighted clustering coefficient of the Web2.0 service network is calculated as 0.594 The standard deviation of the weighted clustering coefficient is calculated as 0.476. The weighted clustering coefficients of the Web2.0 service network range from 0 (theoretical minimum) to 1 (theoretical maximum). Among 216 nodes, 68 nodes have a clustering coefficient of 1, and 35 nodes have a coefficient of 0.

The calculation of the average weighted shortest path length of the Web2.0 service network results in 5.99. The standard deviation of the average weighted shortest path length is 13.443. Because of the large standard deviation, it is hard to say that the average weighted path length characterizes the distance between any nodes.

In order to interpret the measured small-world indicator values (i.e., weighted clustering coefficient and the average weighted shortest path length) of the Web2.0 service network, we compare them with indicator values of artificially constructed small-world networks that have the same number of nodes, the same average node degree, and the same link weight distribution. The artificially small-world network, which we consider, is created using the random redirecting process of Watts and Strogatz [6]. The random redirection process starts with a regular network that has 216 nodes. Each node of this regular network has 8 neighbors.

The link weights are allocated to the links of the network randomly, following the power distribution function $P(w) \sim w^{-2.945}$ where w indicates the weight. This is based on the method of Yang and Yu [13].

The average weighted clustering coefficient $Cl^w(0)$ and the average weighted shortest path length $L^w(0)$ of the regular network (i.e., node degree k of each node is 8 and the rewiring probability p equals 0) are 0.643 and 14.102, respectively. The values of $Cl^w(0)$ and $L^w(0)$ are used for normalizing the values obtained for networks that are derived using different rewiring probabilities p.

As the probability p that a link is redirected increases, the two normalized indicator values decrease (Fig. 2a). While the normalized average weighted shortest path length decreases quickly with small p, the average weighted clustering coefficient keeps a high value until $p \approx 0.10$ before it decreases rapidly as well. Fig. 2a shows that there is a range between $p = 0.01$ and $p = 0.1$ with a high normalized average weighted clustering coefficient (i.e., larger than about 0.8) and a low normalized average weighted shortest path length (i.e., smaller than about 0.6), indicating small-world networks.

The normalized average weighted clustering coefficient of the Web2.0 service network normalized by that of a regular network with a node degree of 8 is 0.924. The normalized average weighted shortest path length is 0.425. The comparison of the two small-world indicators of the Web2.0 service network with the values shown in Fig. 2a suggests that the Web2.0 service network is located in the small-world area (Fig. 2b). In Fig. 2b, the area at the right lower corner is the small-world area that has been defined by Watts and Strogatz vaguely [6]. In addition to this, the Web2.0 service network marks a point almost adjacent to a small-world network. It has to be noted that the curve of small-area networks (Fig.2b) shows a kink in the small-world network area. The location and strength of the kink needs to be analyzed in future research though.

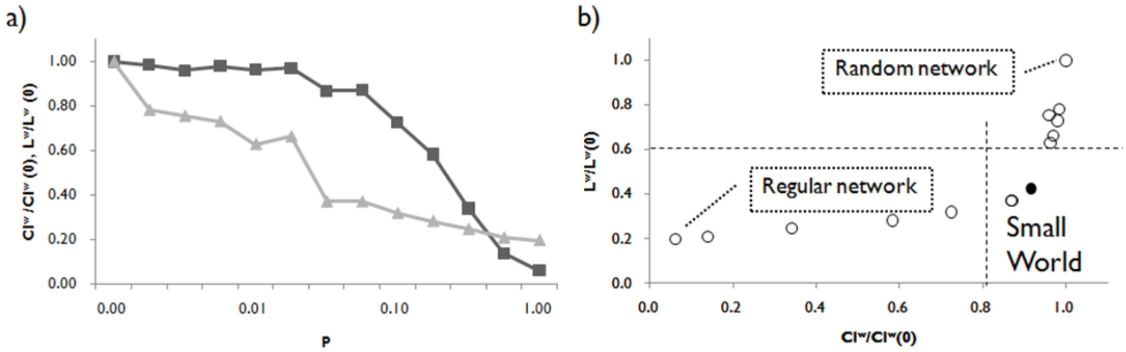

Figure 2. Small-world property of the Web2.0 service network: a) the normalized average clustering coefficient and the normalized average weighted shortest path length of a network generated by the random rewiring mechanism; and b) the relationship between the normalized average weighted shortest path length and the normalized average clustering coefficient for networks generated using the random rewiring process (circle), and for the Web2.0 service network (filled black dot).

3.4. Scale-Free Properties

To examine the scale-free property of the weighted graph of the Web2.0 service network, we use the strengths of node degrees. The cumulative strength distribution of the Web2.0 service network looks like an ordinary scale-free network. The cumulative frequency $P(s_>)$ of strength s decays linearly in the log-log scale coordinate plane (Fig. 3a). The log-log regression of the distribution results in a slope of -0.953, a significance probability of 0.000, and a determination coefficient R^2 of 0.978. That means, it is statistically significant that the weighted graph of the Web2.0 service network has the strength distribution of the power law:

$$P(s) \sim s^{-1.953} \qquad (8)$$

In order to avoid mistaking the exponential decaying for the power law, we draw the cumulative strength distribution in a log-linear scale coordinate plane (Fig. 3b). With a distribution $P(k)$~exp($-\zeta k$), the cumulative distribution $P(k_>)$ can be calculated to be:

$$P(s_>) = \int_s^\infty P(s')ds' = \int_k^\infty \exp(-\zeta s')ds' = \exp(-\zeta s) \qquad (9)$$

If the distribution of the node degree strength is exponentially decaying, the cumulative strength distribution should be linear in the log-linear scale coordinate plane. However, since the cumulative strength distribution in the log-linear scale is convex (Fig. 3b), we conclude that the weighted graph of the Web2.0 service network shows a scale-free property.

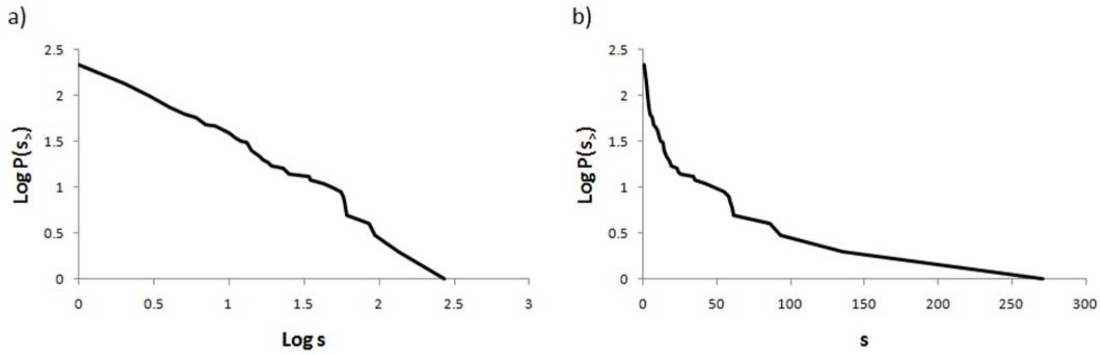

Figure 3. The cumulative degree distribution of the Web2.0 service network in a) the log-log scale coordinates plane and in b) the log-linear scale coordinates plane.

4. Discussion and Conclusion

To analyze the behavioral pattern of the mashup creation on the Web2.0 service network, we measured the average weighted clustering coefficient, the average weighted shortest path length, and the node degree strength of the Web2.0 service network. Based on the analysis results, two conclusions can be drawn: First, the Web2.0 service is a small network as specified by Watts and Strogatz [6]. While the average weighted clustering coefficient of the network is close to the maximum possible value, the average weighted shortest path length is very small in the Web2.0 service network.

Second, the Web2.0 service network has a node degree strength distribution, which looks like a scale-free network. The cumulative strength distribution of the Web2.0 service network significantly fits well into a power function. These results suggest that the weighted Web2.0 service network is an ordinary scale-free network and a small-world network. This result is interesting because it is contrary to the result of the prior research of the Web2.0 service network [18]. Hwang et al. (2009) suggested that the Web2.0 service network has an extraordinarily low exponent of the power law distribution. The difference of our analysis from Hwang et al. (2009) is only how the link weights are calculated. We used Newman’s approach for the weight calculation [10] [25], while Hwang et al. (2009) summed up all creations of mashups for each pair of nodes. This dependency of the network topology on the weighting technique requires further investigation of the Web2.0 service network.

Although we analyzed the pattern of mashup creation in the Web2.0 service network comprehensively, this research involves two limitations. First, self-links within the Web2.0 service network were omitted in this research. Although a new mashup can be generated in two ways, namely by adding value to an existing Web2.0 service (self-link) or by combining several Web2.0 services, we considered the latter one only. Second, we randomly weighted links in the generated complex networks to compare them with the Web2.0 service network. However, we have checked that the node degree strength is correlated with the node degree. To conduct a more proper comparison, we need a weighting scheme which weights links depending on the degrees of two nodes at its end.

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