

THE NETWORK TOPOLOGY OF OPEN INNOVATION FREELANCING

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ABSTRACT

eLancing is an emerging paradigm for outsourcing technical services wherein freelancers bid on projects posted in a large-scale online marketplace. When viewed in concert with other open innovation services such as kickstarter.com, a new networked innovation model is emerging: "very large scale innovation". "Very large scale innovation" networks supported by the Internet are a large-scale form of innovation networks connecting producers and inventors to investors and retailers. In this paper, we study the statistical mechanics of the network structure of the projects and providers in eLancing to ascertain structural preconditions for their effective operation. The unipartite project and provider networks and the collaboration network exhibit the properties of a homogeneous network whereas the associated skill networks exhibit the properties of an inhomogeneous, scale-free network. All of the networks except the provider network are small-world networks. These results point to the lack of coordination and collaboration between providers, which could provide an opportunity for them to pursue more complex projects, and a need for systems integration services.

Keywords: open innovation, networked innovation, collaboration networks

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1 INTRODUCTION

The design and engineering of new products such as Ninja Blocks, ElevationDock, PebbleWatch, and others represents another model of networked new product innovation. In networked innovation, which is already being practiced by engineering firms, a small number of companies collaborate to produce a new product or service (Bergema et al., 2011, Maurer and Valkenburg, 2011). In contrast, a new networked innovation model is emerging from the combination of Web-based services such as quirky.com, to launch product concepts and receive expert and end-user feedback, kickstarter.com, to “crowd fund” product concepts, and freelancer.com, to identify technical experts to implement a product: “very large scale innovation”. “Very large scale innovation” networks supported by the Internet are a large-scale form of innovation networks (Udell et al., 1993). The difference between very-large scale innovation and networked innovation is that new product or service development is no longer necessarily limited to the resources of well-capitalized and resourced firms. Instead, the infrastructure of the Internet and networks of loosely coupled service providers make the technical, social, and financial resources necessary for innovation available to a broad range of individuals. Entrepreneurs and innovators capture innovation through the network infrastructure of the Internet. All that is needed is a ‘good idea’.

Of critical importance to the design engineering part of “very large scale innovation” is assembling the technical experts and skills. Supporting this problem is eLancing, a marketplace of projects and technical and creative specialists. The eLancing marketplace involves a pool of a very large number of projects that are posted by clients and a large community of providers who bid to work on projects (Aguinis and Lawal, 2012). A client then selects a bidder to perform the task(s). The type of technical services offered range from search engine optimization to building sections of Web sites to business development. Testimonials by employers, who are generally small businesses, refer to the value of eLancing in helping them establish new products and services. They cite their lack of spare capacity to separate their innovation-oriented activities from core business operations, which is regarded as a critical step in achieving innovation (Govindarajan and Trimble, 2010).

The eLancing marketplace facilitates connecting providers to projects by matching the skills required for a project and the skills nominated by the providers. This results in the self-guided formation of communities of providers who have similar and possibly shared skills and who are capable of servicing similar projects. Rather than being constrained by local geography for expertise (Brown and Duguid, 2002), eLancing systems provide an ecology within which to find complementary expertise. Large companies have yet, at least publicly, to leverage eLancing for design and engineering technical services. At least one major computer manufacturer utilizes open innovation to source project ideas (Bayus, In Press), though. We believe that product design and engineering firms will begin to consider sourcing specific technical expertise from eLancing sources in the future given that small industrial design firms already source technical expertise from eLancing sources and have launched successful products through these networks.

This model of “very large scale innovation” can involve outsourcing both technical and creative tasks. Employers may have the need for a range of technical services associated with their innovation project. Loosely coupled (because they have no formal business or project relationships) service providers ‘collaborate’ to complete specific tasks associated with the innovation project. Formally, they do not ‘collaborate’ since they neither share information nor resources. However, they may work for the same employer on projects related to a larger project; thus, their collaboration is indirect. The very large scale of collaborators and projects being worked on at any time demands new research approaches to account for the scale of the collaborative community. Obviously, in an ideal freelancing community, there should be compatibility between the capability of providers and the skills needed to perform the projects. Put simply, the *content* of skills required by projects should at least match the content of skills offered by providers. However, beyond this superficial matching of available skills, we question whether certain *structures* of skill sets, projects, and service providers are associated with effective “very large scale innovation”. The particular research question that this paper pursues is the structure of an eLancing community affording an effective networked open innovation service. Based upon prior research in the social networks of small collaborative communities (Uzzi and Spiro, 2005) and the statistical mechanics of large-scale product development task networks (Braha and Bar-Yam, 2004, Braha and Bar-Yam, 2007), we have good reason to believe that particular topological structures of networks of eLancing projects and providers are associated with the effective operation of eLancing

systems. The problem we are solving in this paper is to characterize the properties of project and provider networks of a large eLancing community to contrast structural differences between them, which may lead to inefficiencies in the operation of the eLancing marketplace.

We study the statistical mechanics of the network structure of the projects and providers in eLancing to ascertain potential structural preconditions for their effective operation. In the first study, the topological characteristics of the networks are compared against small-world, scale-free, and random networks to determine the type of network which eLancing resembles. We postulate that the more the structure of the projects and provider networks resembles a small-world network, the more likely the eLancing service would perform effectively. In other words, the small-world network is a structural precondition for effective eLancing networks. Second, we study the minimum number of skills such that the entire network of projects and providers can be connected, producing what is known as a ‘giant cluster’. Finally, we study betweenness centrality and closeness to identify important characteristics such as the central skills.

2 METHODOLOGY

Our perspective is that skills required by projects and the skills made available by providers organize the projects and providers into a network. That is, skills define the connectivity not only between projects and providers but also amongst projects and providers. A network of projects and providers emerge out of the mobilization of skills, as do clusters of providers having complementary expertise (Brown and Duguid, 2002) and projects having complementary requirements. To produce the provider and project networks, we define two bipartite networks. A bipartite network is a network having nodes of two different types. The provider-skill network $G_1 = (P, S, E)$ where P is the set of providers (type-1 node), S is the set of skills (type-2 nodes), and E is the set of the edges between P and S ($E \subseteq P \times S$). A provider in P is connected to a skill in S if the provider has that skill. We define the project-skill bipartite network G_2 in the same way, but now for projects that need a certain skill. We define a third bipartite network, the *collaboration network* $G_C = (P, R, E)$ wherein P is the set of providers, R is the set of projects, and E is the set of the edges between providers and projects. A provider from P is connected to a project in R if the provider has all the skills needed to perform the project. To study the clustering of providers and projects having complementary skills and requirements, respectively, we transform the bipartite networks G_1 and G_2 into four unipartite networks. The graphs G_{PV} and G_{PJ} represent the type-1 set of nodes in G_1 and G_2 respectively. For the type-2 nodes, we define G_{SPV} and G_{SPJ} , wherein two skills are connected if they both exist in a provider or project profile. The networks are constructed as undirected weighted graphs in all our analyses, unless the weight is ignored by the nature of the analysis (e.g., shortest geodesic path between two nodes). The weight of an edge in G_{PV} and G_{PJ} is based on the number of shared skills of two neighbor nodes. In networks G_{SPV} and G_{SPJ} , the weight of edges is defined by the number of times two neighbor nodes (i.e., skills) appear together in a project or provider profile. We consider the networks G_{SPV} and G_{SPJ} to represent the knowledge-map of the providers and projects, respectively.

Any of these networks G can be defined by an equivalent adjacency matrix A , where:

$$\mathbf{A}_{ij} = \begin{cases} d & \text{number of edges between nodes } i \text{ and } j \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

We obtained the data for the network structure of a popular eLancing site using the site’s API. The API allows us to query the database of projects and providers to obtain a dataset consisting of provider and project profiles. These profiles describe the skills required by a project and the skills offered by providers. We removed providers and projects not containing any skills, since these profiles were likely generated either as test projects or provider accounts. We selected ten thousand records, sequentially, from the downloaded profiles of projects and providers.

We study different local and global metrics to study the topological structure of these networks. The first topological characteristic studied is the type of network. Empirical research on the structure of complex networks show that real-world networks can be divided into two classes: homogeneous and inhomogeneous networks (Albert and Barabási, 2002). This classification is based on a single metric: the distribution of the connectivity of nodes $P(k)$, the probability that a node is connected to k other nodes. In a homogeneous network, most nodes have the same number of connections and the number

of edges for any node approaches the average node connectivity. In contrast, in an inhomogeneous network, a small number of nodes are connected to a very large number of other nodes, and most nodes are sparsely connected. These networks are often called scale-free networks.

One of the most intensely studied homogeneous networks is the small-world network. Additional defining characteristics of the small-world network are that there is a short distance between nodes and the nodes are highly clustered (Watts, 1999, Watts and Strogatz, 1998). We believe that a properly functioning eLancing system should have the topological properties of a small-world network. That is, G_C , G_{PV} , G_{PJ} , G_{SPV} , and G_{SPJ} should have the topology of a small-world network. If this were not the case, and the networks were instead scale-free, then the consequence is that, for example, only a few projects can be serviced by a very large number of providers, but most projects can be serviced by only a few providers. This limits the efficiency (competitive bidding) of the marketplace. Other than having a homogenous node degree distribution $P(k)$, two other characteristics define a small-world network: a clustering coefficient and a path length that are higher than a random network of the same node degree (Watts, 1999, Watts and Strogatz, 1998). The clustering coefficient is defined in two ways. The ‘social network’ definition of the clustering coefficient for a network is (Newman, 2010):

$$C = \frac{(\text{number of triangles}) \times 3}{\text{number of connected triples}} \quad (2)$$

Watts and Strogatz propose an alternative local clustering coefficient measure (Watts and Strogatz, 1998). The Watts-Strogatz local clustering coefficient for node i is given by:

$$C_i = \frac{2E_i}{k_i(k_i-1)} \quad (3)$$

where E_i is the number of edges that actually exist and k_i is the number of edges connecting node i to k_i other nodes. The path length is calculated as the mean geodesic distance between nodes in a small-world network (Watts and Strogatz, 1998).

The second topological precondition is the number of skills at which the entire set of projects or providers becomes connected into a single network, or what is known as a ‘giant cluster’. A critical probability p_c exists such that below this probability of a connection between two nodes, the network is comprised of disconnected clusters, but above this value, a ‘giant cluster’ spans all of the nodes (Albert and Barabási, 2002). This value is known as the percolation point. The concept of percolation studies the robustness of a network to removal of its elements (Albert and Barabási, 2002). The removed elements can be either nodes or the connections between them. The former is called site percolation and the latter is called bond percolation. The removal of elements can be performed either randomly or in a targeted fashion to remove the most important elements, e.g., nodes with the highest degree. We study the existence of a percolation point by identifying the number of skills necessary for a ‘giant cluster’ to span the entire network. This minimum skill level, and the skills in this minimum set, is not simply the number and content of skills required by projects; it describes the set of skills at which point any skill, project, or provider can be reached. In the current study, we generate a reverse targeted bond percolation model for networks of providers G_{PV} and projects G_{PJ} . As described before, the edges in these networks are defined by the number of skills shared between pair of projects or providers. We first sort the skills by their popularity among providers and projects. Then, skills are added to the network, one at a time, starting from the least frequent skills. The effect of including certain popular skills in the formation of the ‘giant cluster’ is analyzed and visualized.

Finally, an eLancing system is likely to have some key skills and key providers. To identify those key skills and providers, we studied the betweenness and closeness centrality. The betweenness centrality accounts for the number of paths between two other nodes within which a node lies. To calculate this value, we follow a standard algorithm to calculate the number of geodesic paths between pairs of nodes that pass through a given node (Newman, 2010). Closeness centrality measures the distance, based on geodesic path length, between a node and all other nodes.

3 RESULTS

3.1 Basic Network Properties

We calculated the basic properties of our networks including the number of nodes, edges, and the density of links using Pajek (de Nooy et al., 2012). Table 1 shows the basic properties of our networks

along with three other networks for comparison (Newman, 2010). Empty cells mean that the data was either not available or not applicable to our analysis.

Table 1. Basic properties of eLancing networks and other networks (acquired from (Newman, 2010)) (number of nodes n ; number of edges m ; density δ ; mean node degree $\langle k \rangle$; mean geodesic distance between connected pairs ρ ; clustering coefficient - transitivity C ; mean Watts-Strogatz clustering coefficient C_{WS} ; metrics for similar random network ρ^{rand} and C^{rand} ; small-worldness index S^{rand}

Network	n	m	δ	$\langle k \rangle$	ρ	C	C_{WS}	ρ^{rand}	C^{rand}	S^{rand}
G_I	10424	68021	0.016	13.0	2.94					
G_2	10346	31113	0.009	6.0	3.88					
G_C	20000	2566270	0.0128	256.6	2.09	0.148	0.298	2.47	0	NaN
G_{PJ}	10000	16961830	0.339	3392.4	1.93	0.759	0.824	1.66	0.339	1.92
G_{PV}	10000	54149486	1.082	10829.8	1.46	0.739	0.790	1.0	0.999	0.5
G_{SPJ}	346	4862	0.0814	28.1	2.23	0.343	0.593	2.02	0.079	2.26
G_{SPV}	424	26055	0.290	122.9	1.72	0.576	0.737	1.71	0.290	1.14
<i>Film Actors</i>	449913	25516482		113.43	2.30	0.20	0.78			
<i>Physics Coauthorship</i>	52909	245300		9.27	6.19	0.45	0.56			
<i>Internet</i>	10697	31992		5.98	3.31	0.035	0.39			

There are a few observations to make from results presented in Table 1. The density and mean node degree of networks that involve providers, G_I , G_{PV} and G_{SPV} , are about two or three times higher than the networks that involve projects G_2 , G_{PJ} and G_{SPJ} . Looking at the mean degree of skill network for providers G_{SPV} ($\langle k \rangle = 122.9$) reveals that the higher density and mean degree of said networks is due to the higher number of skills shared by providers, in comparison to the number of skills shared by the projects. Another interesting result in Table 1 is the average node degree of the collaboration network G_C ($\langle k \rangle = 256.6$). Even though there are millions of projects in the eLancing system, and 10,000 providers were selected for this analysis, each provider is qualified to perform only a fraction of the available projects. We will investigate this issue further in the next section in discussing the small-worldness of the collaboration network G_C .

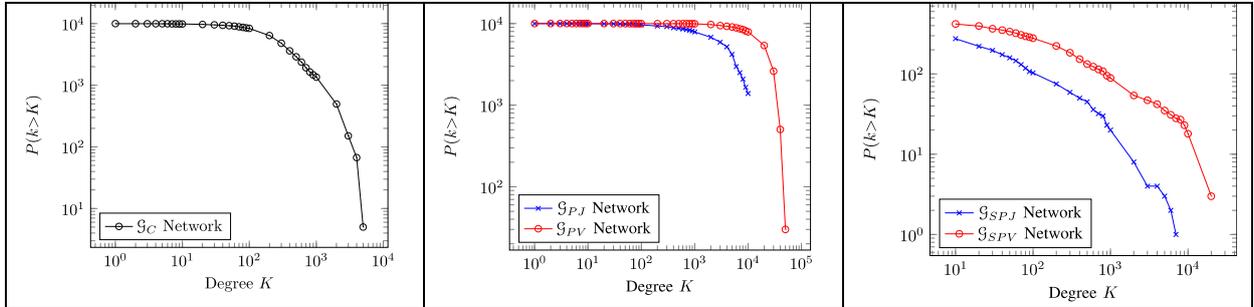


Figure 1. Cumulative distribution of node degree for collaboration network (left), provider and project networks (middle), and skill networks (right)

Second, we tested the node degree distribution $P(k)$, which is the probability of finding a node having k or more connections. Figure 1 shows the plots of the node degree for the G_C , G_{PV} , G_{PJ} , G_{SPV} , and G_{SPJ} networks. We note an unusual pattern. Whereas the G_C , G_{PV} and G_{PJ} networks follow an exponential distribution, which is characteristic of homogenous networks, the degree distributions of the G_{SPV} and G_{SPJ} networks follow a power law, which is characteristic of a scale-free network. In other words, there are a relatively few number of skills in demand in this eLancing market. There will be intensive competition by providers over a few skills, and some providers will enjoy a non-competitive bidding environment for projects requiring the least-requested skills. In contrast, the more homogeneous G_{PV} and G_{PJ} networks imply a behavior wherein projects duplicate the skills required by other projects and likewise providers duplicate the skills offered by other, competing providers. The consequence of this ‘follow the herd’ mentality in terms of describing the skills required to complete a project or the skills available results in projects and providers being connected to many other similar projects or providers, respectively.

3.2 Network Topology

To examine whether the network structures resemble a small-world network, we calculate the mean path length and clustering coefficient of the networks along with basic network metrics using Pajek. Table 1 shows the results of these analyses for our networks and other networks for comparative purposes. All of the networks except G_{PV} satisfy the conditions of a small-world network, which is that its clustering coefficient should be greater than the clustering coefficient for an equivalent random network (Humphries et al., 2006). The most important network that should satisfy the small-world requirement is the collaboration network, G_C . While we find that it does satisfy the small-world network condition, its clustering coefficient is nonetheless small compared to the other eLancing networks, which means that information exchange between projects and providers is less efficient than a network with a higher clustering coefficient. It compares similarly with the film actors network; both networks have about 2 “degrees of separation” between a randomly selected project and a provider or between two randomly selected actors.

To examine the small-worldness properties of the skill networks, we visualize the local clustering coefficient for G_{SPV} and G_{SPJ} . Figure 2 illustrates local clustering coefficient as a function of node degree. In the skill network of projects G_{SPJ} , we find that the nodes with higher degree also have a higher clustering coefficient, which is opposite to many networks (Newman, 2010). Higher clustering coefficient is usually a property of small groups, where the nodes have relatively few neighbors (i.e., low degree), but are highly connected among each other (i.e., high clustering coefficient). The clustering coefficient graph for skills of providers G_{SPV} follows this principle but the graph for skills of projects opposes it.

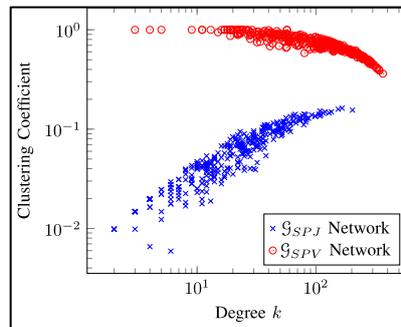


Figure 2. Local clustering coefficient as a function of node degree

There could be different explanations for this result. One interpretation is that there are many projects that are very similar, thus making large groups of interconnected nodes with high degree. Such projects may represent arbitrary breaking down of larger projects into smaller tasks, which are then outsourced via eLancing. This outcome may also result from differences between the nomenclature of skills needed for projects and the skills nominated by the providers. That is, the skills needed by projects have a classification that is different from the classification of skills among providers, even though they have similar names. For example, PHP and HTML skills might be considered two different skills among providers but they always appear as a unit of PHP+HTML in the projects. It may also be that the project employers simply copy existing projects in defining their own. That is, given relatively little guidance as to what skills the providers offer, the project employers simply copy the skills listed in similar projects, which would lead to the high clustering coefficient in the G_{SPJ} network. Regardless of its cause, this difference shows some incompatibility between the skills for projects and providers. The implications of this incompatibility are discussed in conjunction with the results of the other analyses in Section 4.

3.3 Percolation

In this section, we describe the results of the percolation of the G_{PJ} and G_{PV} networks, that is, the set of skills at which point an entire network spans the network of projects and skills. This is the critical set of skills that enables the eLancing system to have a fully connected network of projects with complementary skill requirements and providers with complementary skills. There are 346 distinct skills listed in project records and 424 distinct skills listed in the provider records. The rate of change of the size of the giant cluster and the percolation threshold characterize the sensitivity of the

connectivity of the networks to the removal of skills. Loss of connectivity results in the isolation of a project or a provider from the rest of the network. To produce the percolation model, we follow the procedure associated with reverse targeted bond percolation (Albert and Barabási, 2002, Newman, 2010). We first sorted all of the skills based on their frequency of appearance. Then, we incrementally add one skill, starting from the most frequently requested or provided skill, to a null G_{PJ} and G_{PV} network, wherein the addition of the skill results in the establishment of associated edges in G_{PJ} and G_{PV} . Initially, the size of the largest cluster in the null networks is 1 because all nodes are isolated. Then, we begin to connect the nodes by adding one skill at a time, starting from the least frequent skill. We continue to add skills to the networks until all the skills have been added. At each step, we calculate the size of the ‘giant cluster’.

Figure 3 presents the size of the giant cluster in each step of adding in an additional skill to the networks. As Figure 3 illustrates, the size of the giant cluster starts to grow after including about 150 skills. However, the growth of the giant cluster in the projects network G_{PJ} is faster than in the providers network G_{PV} . The size of the giant cluster in the provider network continues to grow slowly until about 400 skills are included and then shows a sharp rise until the end. There are only a few skills responsible for the integrity of the network, and the network is highly vulnerable to removal of those skills. In other words, there are skills that one provider should have if one provider wants to be accepted in the community of providers and be able to bid on many projects. In contrast to the providers network, the projects network percolation model shows a more *resilient* behavior. The removal of each skill will reduce the size of the giant cluster by a fraction (i.e., isolate some projects), but the network retains its structure and has an overall resilience to removal of skills.

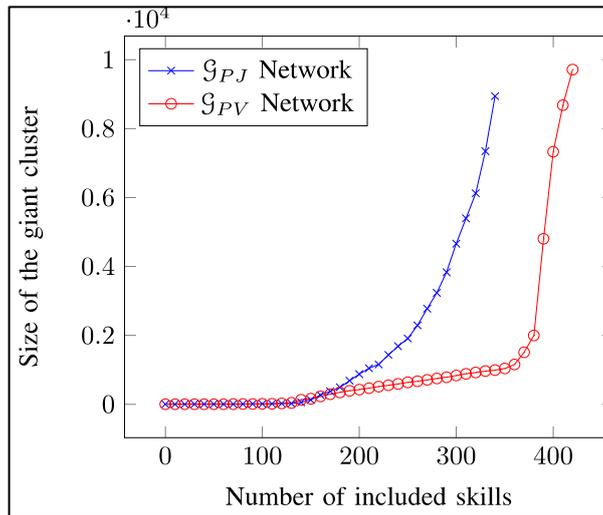


Figure 3. Reverse targeted bond percolation model for networks G_{PJ} and G_{PV}

3.4 Centrality and Important Skills

In this section, we examine the networks on a local scale to find out whether there are important (i.e., central) skills that cause the different behaviors of the projects and providers networks on the global scale. To test whether there is a simple overlap between most requested skills and most widely available skills, Figure 4 illustrates the top ten popular skills offered by providers and required by projects. The proportional sizes of the nodes (circles) represents the relative number of skills requested/offered and the gray scale intensity of the edges represents weight of connection between each pair of skills. As this figure shows, there are triplets of skills with high popularity that also appear with each other frequently. For example, many providers include ‘‘Data Processing’’, ‘‘Excel’’, and ‘‘Data Entry’’ in their skill list. This causes specific motifs to emerge among communities of providers or projects where triplet clusters of skills tend to appear frequently.

To identify the distribution of the critical skills in each network, we compute, with Pajek, two additional metrics of the centrality of nodes in addition to node degree described previously: betweenness centrality and closeness. Betweenness centrality counts the number of geodesic paths that pass through each node (Borgatti, 2005) on the premise that important nodes have many paths through them. The study of betweenness is founded upon the concepts of flows in the networks. This is not

specifically relevant to our networks of providers G_{PV} , projects G_{PJ} , or skills G_{SPV} and G_{SPJ} , because there is nothing being passed within each network except a flow of projects (i.e., tasks) to the providers. However, Freeman (Freeman, 1979) suggests applying the betweenness centrality not only as a measure of flow but also as a way of examining the network's structural connectedness. We examine the betweenness centrality to compare their general connectedness. Closeness measures the distance between a node and all other nodes. Central nodes have very short paths to all other nodes.

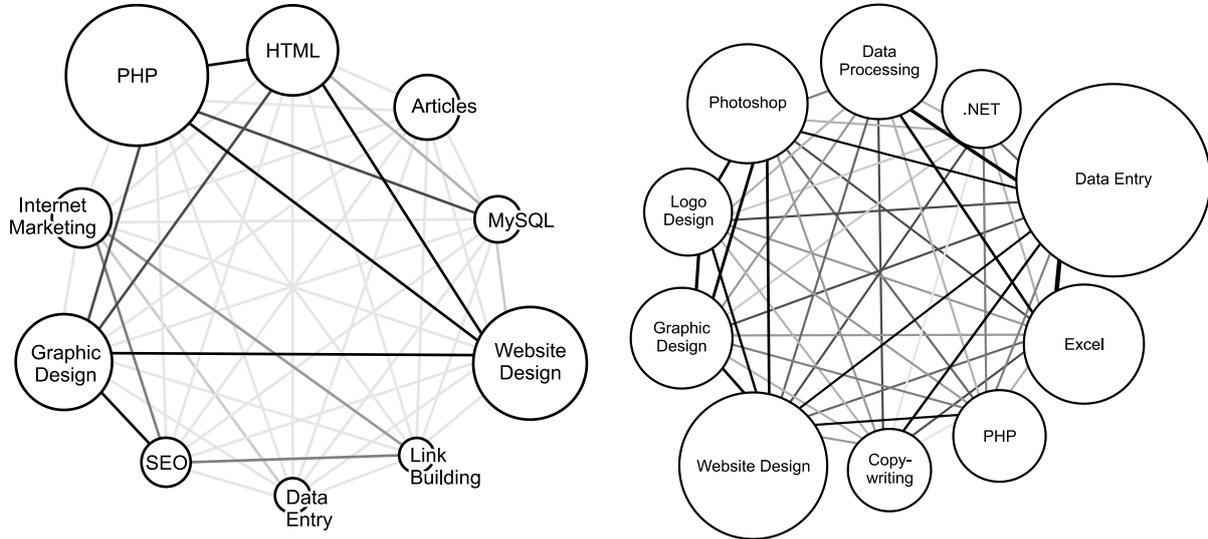


Figure 4. Ten most frequent skills required by project (left) and offered by providers (right) and their weighted connections

Figure 5 illustrates the cumulative distribution of betweenness centrality for the unipartite networks. The network betweenness centralization, a measure of dispersion or inequality of betweenness, of the provider skills network G_{SPV} is 0.021 compared with a value of 0.123 for G_{SPJ} , which is one order or magnitude higher. In terms of local properties of nodes, G_{SPJ} has about 10 nodes with a betweenness higher than the nodes with high betweenness in the network of provider skills G_{SPV} . This means that the project skills network is more structurally connected than the provider skills network, confirming the percolation results.

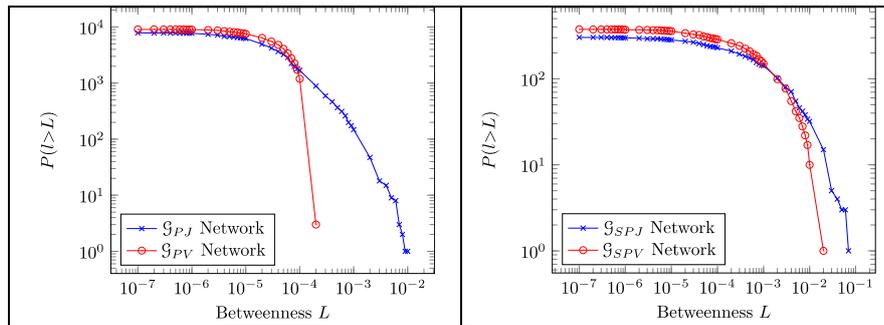


Figure 5. Cumulative distribution of betweenness centrality for provider, project, and skill networks

Table 2 lists skills ordered by betweenness centrality in each network. Note that the value of closeness is reported such that the higher the value of closeness, the closer all other nodes are to the reported node. We find a correlation between these two measures of centrality. As the results in this table indicate, there is a fairly strong mismatch between the most central skills requested and the skills provided. One problem is that the level of granularity of the skills is not equivalent. HTML, PHP, Javascript and MySQL are skills relevant to Website Design; likewise Photoshop is relevant to Graphic design. Yet, they are listed as independent skills. This mismatch suggests that both employers and providers should be clearer as to whether they require/provide. We note the project skills network shows a preference by employers for component skills rather than comprehensive services. For

example, the component skills PHP, HTML, Javascript, and MySQL are related to Website Design; of these component skills, only PHP and Javascript are central skills in the provider skill network G_{SPV} .

Table 2. Most important skills in G_{SPV} and G_{SPJ} networks based on betweenness

G_{SPV} Skills	Degree	Closeness	Betweenness	G_{SPJ} Skills	Degree	Closeness	Betweenness
Data Entry	27677	0.8807	0.0229	PHP	7435	0.6952	0.1266
Photoshop	20486	0.8369	0.0189	Website Design	6178	0.6443	0.0657
Excel	19079	0.8386	0.0173	Graphic Design	4841	0.6263	0.0622
Website Design	25155	0.8303	0.0173	HTML	5120	0.593	0.0332
Graphic Design	17504	0.8127	0.0159	Javascript	1948	0.5807	0.0243
PHP	17042	0.8111	0.0147	Internet Marketing	2896	0.5718	0.0231
Data Processing	18186	0.8096	0.0127	MySQL	2674	0.5708	0.0204
Logo Design	15378	0.7839	0.0111	SEO	2181	0.5757	0.02
Javascript	14414	0.7626	0.0098	Articles	2595	0.5335	0.0105
Banner Design	13701	0.7464	0.0079	Article Rewriting	1744	0.5187	0.007

The differences between betweenness centrality of providers network G_{PV} and projects network G_{PJ} is more obvious. There are many nodes in the G_{PJ} network that have a betweenness value higher than the maximum seen in G_{PV} network. The implication is that there is a high degree of competition between providers for a set of central skills, but only a few skills are central to providers.

Table 3. Five projects and providers with highest betweenness centrality in G_{PV} and G_{PJ}

	Record No.	Skills Count	Degree	Betweenness	Closeness
G_{PV}	PV1003336	25	47167	0.0002	0.8800
	PV1016726	24	65964	0.0002	0.8807
	PV1012521	19	41580	0.0002	0.8987
	PV1001728	23	41768	0.0002	0.8435
	PV1016209	20	45770	0.0002	0.9070
G_{PJ}	PJ1008031	5	15799	0.0103	0.6739
	PJ1008915	5	9053	0.0088	0.6218
	PJ1008914	5	11267	0.0077	0.6199
	PJ1012436	4	7450	0.0069	0.6091
	PJ1000122	5	11215	0.0068	0.6225

4 DISCUSSION AND CONCLUSION

This paper presented an empirical analysis of an eLancing site through the lens of complex networks. We demonstrated how the properties of small-world networks, percolation, and centrality provide valuable insights on the relation between the topology of eLancing as an innovation network and the performance of the network. We found some surprising results in studying the network structure of eLancing. Whereas the unipartite project and provider networks and the collaboration network exhibit the properties of a homogeneous network, the associated skill networks exhibit the properties of an inhomogeneous, scale-free network. A few skills are in high demand, but most skills are not important. Also, all of the networks except the provider network G_{PV} are small-world networks. Thus, while the projects and skills are efficiently connected to each other in a small-world topology, the providers are not. The loose connectivity of the provider networks is confirmed by its lower betweenness centrality. This result points to the lack of coordination and collaboration between providers, which could provide an opportunity for them to pursue more complex projects. Finally, the percolation behavior of the G_{PV} network shows that about 1/3 of the skills provided are not actually essential to the operation of the eLancing site.

Based on the findings of this study, we claim that the small-world structure of the projects and provider networks best supports an effective eLancing service. However, while topological properties may produce structural preconditions on the effectiveness of eLancing, we have only begun to

examine the performance of the eLancing. Specifically, we do not yet correlate the structural properties to the actual performance, such as the feedback provided by employers to providers and the number of bids placed on projects. Future studies will consider these factors to further identify the topological preconditions for an effective eLancing system. The ecosystem of eLancing provides a valuable source of data for the study of innovation networks, especially in the establishment of metrics to characterize the relationship between the topology of the networks and their behavior. Such information can then be translated into studies of innovation networks in “bricks and mortar” business. Based on the research design of this study, knowledge-oriented transactions between companies would provide the most valuable insights into the effectiveness of their network organization.

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