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Social Network Modelling

E. Pugacheva[1]

Abstract. In the offered review some key issues of social network analysis are discussed. This is a brief summary of social network characteristics, models of network formation, and the network perspective. The aim of this overview is to contribute to interdisciplinary dialogue among researchers in physics, mathematics, sociology, who share a common interest in understanding the network phenomena.

Key words: social networks, random graph, small-world model, preferential attachment, social capital, structural holes, structural equivalence.

1 Introduction

Social network analysis is one of the most recent developments of sociology engaged in studies of social links arising in the course of social interaction and communication. Contemporary theory of complex networks, or network science for short, has vividly demonstrated productivity of interdisciplinary approaches. Thus, mathematics and sociology are the historical roots of network science. Mathematicians study various properties of abstract structures called graphs made of nodes and edges. Sociologists have developed more applied aspect of network science, namely Moreno's sociometry. However, it was physicists who revealed a number of properties of real networks that escaped from the field of view of social scientists and mathematicians. The ideas of small-world (Watts & Strogatz, 1998) and scale-free networks (Barabasi & Albert, 1999) published in the late of 1990's happened to be fruitful and produced new perspectives and analytical tools to study various systems, including biology, sociology, economics, political science, management science, and more.

Undoubtedly, in the future the success of social networks modeling will be to a great extend determined by the efficiency of interdisciplinary dialogue between representatives of different scientific fields (Pugacheva, 2003). The social networks simulation needs joint efforts and constructive interactions from the very beginning when the problem is formulated on the basis of empirical data (network of colleagues, friends, acquaintances, Internet, etc.) till the end when the conclusions are made and the results are interpreted.

Thus, computer scientists help to understand and design complex networks; social scientists focus the attention on human behavior; economists revise views of economic rationality; biologists research neural and gene networks;

[1]Associate Professor of Adult Education Department National Pedagogical Dragomanov University.

physicists and mathematicians are interested in the theory of macroscopic behavior (phase transitions, bifurcation, self-organization, etc.).

Today social networks have been investigated on three levels: theoretical (network formation, dynamics, design, network influence on social behavior and vice versa, coevolution); empirical (network patterns, regularities), methodological (how to measure and analyse networks).

2 Basics of networks

Social networks describe social relationships between people. Interdisciplinary nature of network science reflected in the terminology. So, mathematicians use graph/vertex/edge, physicists use "network/node/edge", computer scientists use "network/node/link", social scientists use "network/actor/tie", etc. As to the difference between "network" and "graph", researchers point out that "network" refers to real systems (www, social network, metabolic network), while a "graph" emphasizes more on its aspect as an abstract mathematical object (web graph, social graph). Very often it is considered that distinction of these terms isn't so essential and they are used as synonymous (Sayama, 2015; Barabasi, 2014).

The model of social network is a graph where social actors stand for nodes and social links represent edges. In broader sense social actors are not only individuals, but also social groups, organizations, business-units, cities and countries. Similarly, links are any "connection of interest" between the actors. Examples of social networks include network of friends on Facebook, network of co-authorship of scientists, cooperation network, citing in scientific articles, e-mail network of contacts and business relationships.

Social network is a set of the dyadic ties between social actors. The distinctive feature of social scientists lies in division dyadic relations into different types. For example, the classic typology includes four basic types: similarities (location, membership, attribute), social relations (kinship, social role, affective, cognitive), interactions (talked to, advice to, helped, etc.), flows (information, beliefs, resources, etc.).

Social scientists typically view each kind of tie as a separate network, each with a potentially unique structure and different implications for the nodes involved. For example, the advice network in a corporate office may have a radically different structure than the friendship network for the same nodes. Rather than searching for a single, "best" relation to serve as an indicator of the social network, researchers typically measure multiple relations and examine how they relate to each other (Borgatti, et al., 2009, p. 9). In other words, content matters.

To observe the basic definitions of network science let's define $G = (V, E)$ as an ordered pair of sets, where V is the number of nodes or vertices and E is the set of links or edges. We will use N to denote the number of vertices in a network. The number of possible edges:

$$\frac{N(N-1)}{2} \approx \frac{N^2}{2}.$$

In network analysis the special attention is paid to network and nodes characteristics. The following metrics are the basic characteristics of nodes.

Degree Centrality is the number of edges connected to a node. This indicator shows "How connected is node?" and reveals the most active actors in the social network, as well as determine which nodes can play a central role in disseminating information.

Betweeness Centrality describes node's role as an intermediary or connector. Sometimes it is very important to determine the relative importance of nodes that form given network. This indicator is calculated according to the formula:

$$B(i) = \sum_{st} \frac{\sigma_{st}(i)}{\sigma_{st}},$$

where $\sigma_{st}(i)$ is the number of shortest paths from the node s to node t via node i, and σ_{st} is the total number of shortest paths between nodes s and t. Calculating the coefficients for each of the nodes one can determine the node that has the highest probability of dissemination of information. This indicator may also be useful in determining the nodes whose removal might break the network.

Closeness Centrality shows how easy to reach other nodes from given one. It can be calculated as the average length of all shortest paths from the node to the other nodes of the network:

$$C(i) = \sum_{j=1}^{N} \frac{d(i,j)}{N-1}.$$

Knowing the value of this parameter, one can determine how long the information will come from the node to the other vertices. The lower the value, the faster the node gets information.

Eigenvector Centrality distinguishes more "influential" nodes. This coefficient indicates whether the node is connected with those who have a lot of connections. It is useful to rank the importance of a node in the network (e.g. Google Page rank: score of a page is proportional to the sum of the scores of pages linked to it).

For example, consider staff network shown in Fig. 1. Links between two network nodes imply two-way communication, through which employees share knowledge and information. As one can see employee D has highest number of links. This signifies the highest activity of this employee. However, the influence of employee D should not be overestimated. The circle of his/her communication is limited to a closed circle of the nearest neighbours. Employee H is less active (only 3 contacts, which is less than the average for the network), but it is the strongest node in the network. Employee H is the only connector between cluster of node D and nodes I and J. Employees of F and G are also less active than the D, but the pattern of their ties allow them to reach quickly all other nodes in the network. In addition, the high value of the eigenvector centrality signifies high ranting of these employees.

As consultant in network analysis Valdis Krebs argues (Krebs, 2000), the golden rule of realtors "Place, place, place" matters in virtual networks.

Network structure is the second key issue of network analysis. Network characteristics allow analyzing the patterns of interaction, vulnerability, network effects. First of all, it is network connectivity that could be described by network degree, path length, and average path length and network diameter.

Label	***Degree Centrality***	***Betweeness Centrality***	***Closeness Centrality***	***Eigenvector Centrality***
A	4	0,83	1,89	0,73
B	4	0,83	1,89	0,73
C	3	0,00	2,00	0,59
D	**6**	3,67	1,67	1,00
E	3	0,00	2,00	0,59
F	5	8,33	**1,56**	**0,83**
G	5	8,33	**1,56**	**0,83**
H	3	**14,00**	1,67	0,42
I	2	8,00	2,33	0,11
J	1	0,00	3,22	0,03

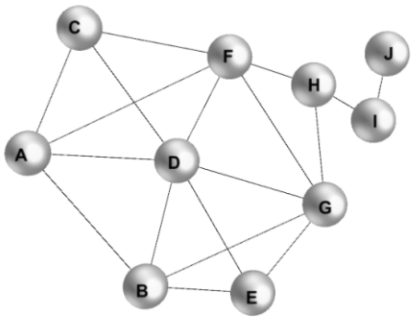

Fig. 1. Network analysis example

Network degree is the average degree of all network nodes and can be calculated as: $k_{av} = 2E/N$. *Path length* between nodes i and j is the smallest number of edges connecting them. This indicator helps to find the shortest way to transmit information.

Average path length of a network is the average path length over all pairs of N nodes:

$$l_{av} = \frac{2}{N(N-1)} \sum_{i<j} l_{ij}.$$

Network diameter l_D is the maximal path length between two nodes $D = \max l_{ij}$. Network diameter shows the maximum time necessary to disseminate information in the network.

The key metrics have the following property: $1 \le l_{av} \le D \le N-1$. An interesting result was formulated as the theorem on network structure (Bollobas, 1981; Chung & Lu, 2002; Jackson, 2008): *If* $k_{av}(N) \ge (1+\varepsilon)\log N$, *for some* $\varepsilon > 0$ *and* $\frac{k_{av}(N)}{N} \to 0$, *then, for large* N *average path length and diameter are approximately proportional to* $\frac{\log N}{\log k_{av}}$.

The theorem on network structure correlates with Stanley Milgram's result known as "Six Degrees of Separation" (Milgram, 1967). Thus, if the world population is approximately 6,7 billion, an average number of contacts (friends, relatives,..) is about 50, than the average path length is $\frac{\log(6,7 \times 10^9)}{\log 50} \approx 6$.

The next important characteristics of networks are density and clustering. The *density* of network is defined as

$$p = \frac{E}{N(N-1)/2},$$

where E is the total number of links in network and $N(N-1)/2$ is the number of possible links. This coefficient is a measure of how well the network is connected. The highest score of 1 is in fully connected graphs, called cliques.

At the same time giant interconnected networks are characterized not by high density but by high clustering, as it is typical for friendship, cooperation, and social groups. *Clustering coefficient* shows what fraction of your neighbors is connected. To be more exact, clustering coefficient of node u is

$$c(u) = \frac{\text{actual number of links between neighbors of } u}{\text{max possible number of links between neighbors of } u}.$$

In terms of social networks clustering means that "friend of my friend is my friend". *Clustering coefficient of a network*, G labelled as $CC(G)$ is an average of $c(u)$ over all nodes u in G.

Real social networks are often fragmented into groups or modules. *Modularity* is the ratio of the number of links within the community to external links.

As empirical researches demonstrated, the large-scale social networks exhibit:

1) small diameter;
2) small number of connected components;
3) high clustering coefficient;
4) heavy-tailed degree distribution.

Small diameter implies that network diameter equals 5 distances between nodes, which corresponds to the six degrees of separation of Stanley Milgram.

The statement "high clustering" needs some consideration. Clustering coefficient of a network $CC(G)$ measures how likely nodes with a common neighbor are to be neighbors themselves. If we picked a pair of nodes at random in G, probability that they are connected is $p = \frac{E}{N(N-1)/2}$, where E is a total number of links in G. So, clustering is high if $CC(G) \gg p$.

3 Models of social network formation

Random graph model. Initially complex network was considered as random graph. This model is based on the publications of Erdös and Rényi (Erdös & Rényi, 1959). The algorithm for generating random graph could be described as follows: begin with N isolated nodes, then gradually (one at a time) link two randomly selected nodes that are not already neighbors. The key parameters of the model are:

1) N — number of nodes;
2) p — probability that two nodes would be connected.

Some properties:

1. Average number of links $E_{av} = p\frac{N(N-1)}{2}$;
2. Average node degree $k_{av} = p(N-1)$;
3. Number of nodes at distance l is $N(l) = k_{av}^l$. At the same time $N(l)$ must not exceed the total number of nodes in the network. For $l = l_{av}$ an approximation $N(l_{av}) = N$ takes place (Barabasi, 2014, p. 22). Therefore, $l_{av} = \frac{\log N}{\log k_{av}}$ or $l_{av} \sim \log N$, $N \gg 1$. So even rapid growth of network nodes does not significantly affect the change in the average distance between nodes, indicating that a random network has the property of small diameter.

Phase transition is the next interesting phenomena of Erdös–Rényi model. At some critical point $k_{av} = 1$ there is a significant jump in the size of largest component (Fig. 2)[1]:

$k_{av} < 1$: many small subgraphs;
$k_{av} > 1$: giant component + small subgraphs.

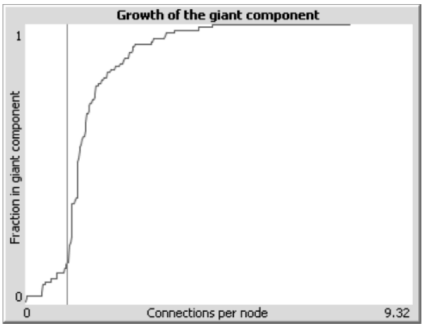

Fig. 2. Threshold phenomena in Erdös–Renyi Model

Thus the random network model predicts that the emergence of a network is not a smooth, gradual process. Threshold phenomena mean that isolated components collapse into a giant component. On the other hand, random networks quickly break down into isolated fragments with random node failure. In other words, random networks are vulnerable to random attacks.

Random network analysis revealed another important result: despite the fact that the connections are random, most nodes have approximately the same number of links.

Probability that node i has exactly k links is the product of three terms: the probability that it is connected to k nodes; the probability that it is not connected to other $(N-k-1)$ nodes; and the number of ways we can select k links from $N-1$ potential links a node can have. Therefore, the degree distribution of a random network follows the binomial distribution $p_k = C_{N-1}^k p^k (1-p)^{N-1-k}$. For large networks the degree distribution is well approximated by Poisson distribution with exponential decay from mean (Fig. 3). As such, in a large

[1]Wilensky, U. (2005). NetLogo Giant Component model. http://ccl.northwestern.edu/netlogo/models/GiantComponent. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.

network the degree of most nodes is in narrow vicinity of k_{av}. This statement conflicts with real social networks.

Clustering coefficient of a network could be calculated as a ratio of the average number of links

$$E_{av} = p\frac{N(N-1)}{2}$$

to maximum number of links $\frac{N(N-1)}{2}$. It is easy to see that clustering coefficient of random network equals p. To summarize, random network model doesn't capture high clustering of real networks.

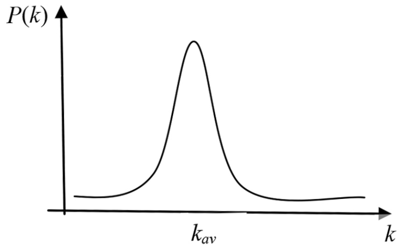

Fig. 3. Degree distribution $P(k)$: probability that a node has k links

As a result, Erdös–Rényi model explains giant component and small diameter. At the same time it doesn't explain such properties of real social network as:

— degree distribution not heavy-tailed;

— clustering coefficient is not high (exactly p).

In the early 2000's it was recognized that Erdös–Rényi model is not good in description real social networks such as Facebook, Twitter and so on. For example, according to the theory of random networks in the society of $N = 7\times10^9$ individuals a typical individual has between 986 and 1032 friends. There are no highly popular persons. At the same time a study of Facebook network shows that a numerous individuals have about 5000 friends (Barabasi, 2014).

Watts–Strogatz (WS) small-world model. In 1998 Duncan Watts and Steven Strogatz (Watts & Strogatz, 1998) proposed the model that has both low average path length and high clustering coefficient. The WS model is a hybrid network between a regular lattice and a random graph. The idea of WS network is in rewiring a regular lattice (Fig. 4) into a random graph by reassigning with probability p an original lattice edge at random (Fig. 5). The process of such rewiring slightly changes the clustering coefficient (nodes continue seeing mostly the same neighbors), but original average path length drops rapidly for low p (Fig. 6)[1]. Thus WS model displays the small-world effect: low average path length and "6 degrees of separation".

At the same time WS model still has Poisson degree distribution and that is why belongs to exponential networks. Small-world model better explains the characteristics of a social network. Nevertheless, peak degree distribution near the middle is unusual for many real networks.

Preferential attachment model. In 1999 Albert–László Barabási and Réka Albert (Barabasi & Albert, 1999; Albert & Barabasi, 2002) suggested the following model:

1) number of nodes in the network is not fixed; a node is added at each step;
2) new is linked with higher probability to a node that already has a large number of links: "rich-get-richer".

[1]The model and documentation was adapted by Eytan Bakshy and Lada Adamic from: Wilensky, U. (2005). NetLogo Small Worlds model. `http://ccl.northwestern.edu/netlogo/models/SmallWorlds`.

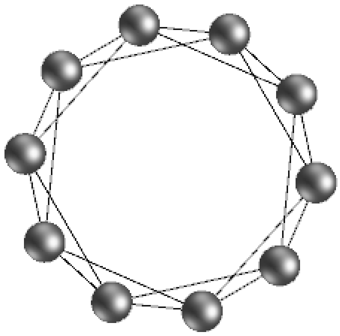

Fig. 4. Ring lattice ($K = 4$)

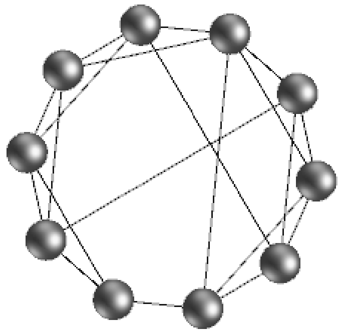

Fig. 5. Watts–Strogatz Model

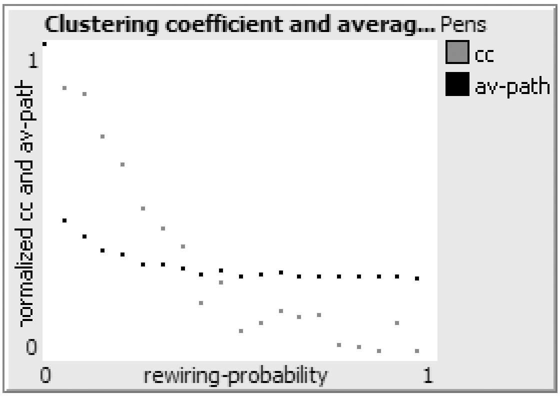

Fig. 6. Clustering coefficient and average path length as a function of rewiring probability p

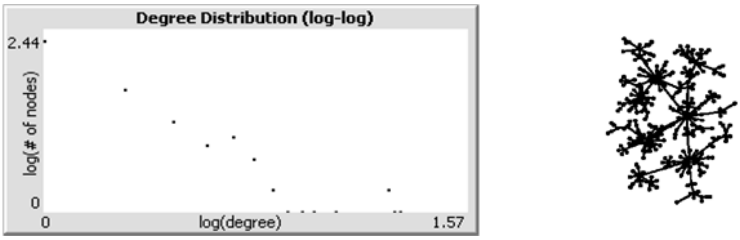

Fig. 7. Preferential attachment model

The probability that a new node will be connected to node i depends on the connectivity k_i of that node $P(k) = \dfrac{k}{\sum_i k_i}$.

The mechanism of preferential attachment is an example of positive feedback. The node which occasionally gets more links begins to grow rapidly. This effect is called "rich get richer" (Fig. 7)[1]. As a result, the probability of deviation is higher than in the case of a normal distribution. There is small number

[1]Wilensky, U. (2005). NetLogo Preferential Attachment model. `http://ccl.northwestern.edu/netlogo/models/PreferentialAttachment`. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.

of highly connected nodes (hubs) in the tail of distribution. At the same time in the head of the distribution one can find a great majority of nodes with few connections.

Rich-get richer process generally leads to heavy-tailed distribution adhere to power law $P(k) \sim k^{-\lambda}$ (Fig. 8). Such networks are called scale-free networks because the function of probability is scale invariant. Thus, multiplying argument by a constant causes only proportionate scaling of the function itself: $P(bk) = (bk)^{-\lambda} = b^{-\lambda}k^{-\lambda}$.

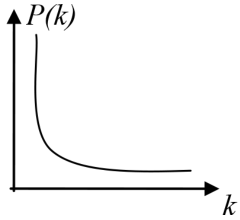

Fig. 8. Power law distribution

Scale-free networks fairly good describe technological networks, social networks, biological networks, etc. (Fig. 9)[1].

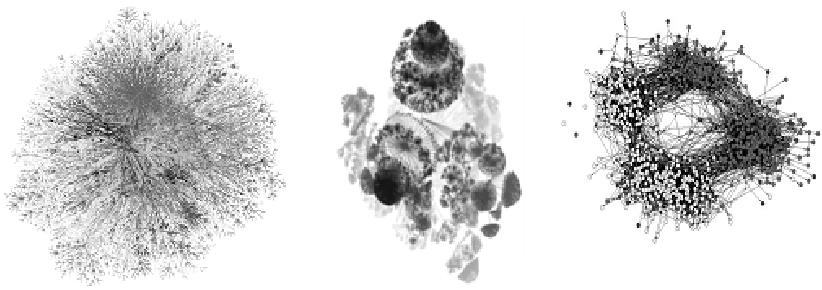

Fig. 9. Some examples of networks: Internet; citation networks; friendship net

Network analysis revealed that networks of different nature are more similar that one might have expected (Newman, 2003).

Basic statistics for a number of networks

Network	Average path length (l_{av})	Exponent of degree distribution if the distribution follows a power law (λ)	Clustering coefficient (CC)
Film actors	3.48	2.3	0.78
Email messages	4.95	2	0.16
Internet	3.31	2.5	0.39
Electronic circuits	11.05	3	0.03
Metabolic network	2.56	2.2	0.67

Network anatomy is very important because structure affects function and vice-versa. Network analysis helps to approach such knotty problems as

[1]Examples of networks are taken from Leigh Tesfatsion "Introductory Notes on the Structural and Dynamical Analysis of Networks" `http://econ2.econ.iastate.edu/classes/econ308/tesfatsion/NetworkNotes.ModifiedZhou.pdf`

prevention of disease spreading, control of information diffusion (marketing, rumors, fads, etc.), understanding robustness and stability of complex technological networks.

Majority network processes are similar in nature and permit universal description. It is necessary to bear in mind that scale-free networks have higher (in comparison with random networks) speed of diffusion processes and possibility of snowballing processes (Fig. 10). The undoubted advantage of scale-free networks is their robustness against random failures. However they are vulnerable to targeted attacks on their hubs.

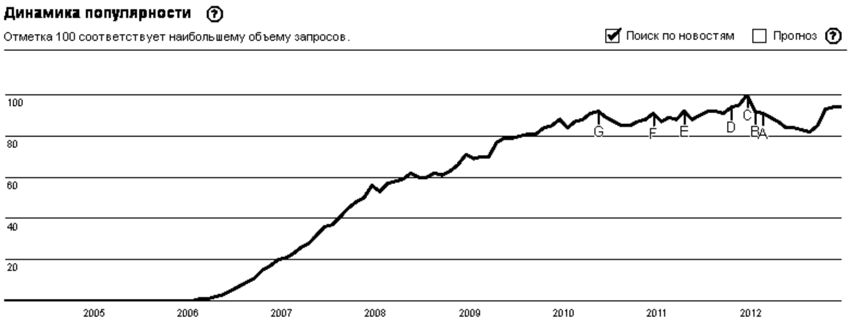

Fig. 10. Rapid growth of YouTube popularity

4 Some results of social network analysis

The key idea of social network theory is embeddedness of social actors in webs of social interactions and relations. Conceptually society is considered not as a monolithic entity but as a pattern (network) of social relations that emerge as a result of social interactions. The fundamental axiom of social network analysis is the notion "network matters" (Granovetter, 1985; Uzzi, 1996; Coleman, 1988).

The main tasks of social network analysis are (Borgatti, et al., 2009):

1) network structures analysis (at the network level);
2) network positions analysis (at the node level);
3) dyadic properties study (at the dyad level).

At the network level of analysis, two properties are of special attention: cohesion and shape. Cohesion refers to the connectedness of the structure and includes properties such as density, path length, and modularity.

Shape refers to the distribution of ties and presumes simulation of network effects. Experiments in behaviour games at the University of Pennsylvania show that network structure matters Last researches have shown (e.g. (Kearns, Judd, & Wortman, 2009) that well-connected minority can impose their preference on the majority. The structures under investigation differ qualitatively in various ways depending on nature of connectivity (from Erdös–Rényi model to preferential attachment) and ratio of inter-group and intra-group links. The key finding of the experiments is that in some network topologies (e.g. preferential attachment) minority preference consistently wins globally. It was also shown that not only well-connected minority reliable takes priority over the majority preference but that such a group can facilitate global unity.

Another interesting result was obtained during investigation of coloring problem (a social differentiation task) and consensus (a social agreement task) in different network topology (Judd, et al., 2010).

The coloring problem requires each player in a network to choose a color from a fixed set that differs from the choice of their network neighbors, while consensus requires selecting a color that agrees with all network neighbors. Despite of cognitive similarity, these tasks demonstrates opposite behavioral effects within social networks with different structure. It was shown that as the networks become less clustered and more random, decentralized coloring becomes more difficult to solve, while decentralized consensus becomes easier. The authors of experiment concluded that network properties (degree, centrality) alone are not sufficient to explain the observed patterns in collective behavior. Thus the task itself is of vital importance, even between two cognitively similar tasks. In other words, the task should match network structure.

Modern researches at network level are dedicated to analysis of diffusion process (Easley & Kleinberg, 2010), collective actions (Watts & Strogatz, 1998), innovation and network games (Jackson, 2008).

Analysis at the level of the nodes allows revealing the potential power of social actors. The key contribution in this area of research is the theory "Strength of Weak Ties" developed by Mark Granovetter (Granovetter, 1973). According to this theory, people establish strong contacts with those who have similar socio-economic characteristics. This leads to information redundancy because communication channels transmit identical information. Conversely, weak contacts as a source of novel information could open access to new resources. According to Granovetter, people need a network that is low on transitivity.

Based on the theory of weak ties American sociologist James Coleman (Coleman, 1988) proposed theory of social capital. The concept of human capital includes individual's competencies and resources (e.g., intelligence, education, experience). Social capital is considered as the resources that individual can mobilize through others + the way in which his/her connections to others facilitate achieving individual goals. So, social capital is the way that connects the various forms of human capital.

Consultant on social networks Valdis Krebs argues that "in today's knowledge organization, the goal expands to "hire-and-wire"— to hire the best people with the best network and integrate them into the value chain so that their combined human and social capital provide excellent returns" (Krebs, June 2000, p. 89).

The theory of social capital theory was developed by American sociologist Ron Burt in the theory of structural holes (Burt, 1992). Structure holes are defined as disconnections in social network. Burt argues that the more "structural holes" in the ego-network of the actor, the greater his/her competitive advantage. In this situation broker who connects different network communities can control the behaviour of others, selectively hiding or providing information. Cohesion, leading to the closure of the group, can overcome trust and cooperation problems. At the same time structural holes give entrepreneurial possibilities. The theory of structure holes has been successfully used in business consulting. As such, for successful innovation one needs both to overcome trust and cooperation problems and entrepreneurial possibilities, so to combine structure holes and closure in a single network.

Dyadic analysis examines the structural equivalence of nodes. Equivalence refers to the extent to which pairs of nodes play similar structural roles in the network. The idea is in building reduced models by collapsing together nodes that are structural equivalent. In this new network the nodes represent structural positions rather than individuals (Lorrain & White, 1971). It was observed that structurally equivalent actors are faced similar social environment and demonstrate similarities in behaviour.

Generally speaking, the modeling of social networks aims to explain the process of network formation and to predict its properties. A variety of approaches to explain network formation can be divided into two classes: opportunity-based and benefit-based. The first approach is based on the probability of establishing a link between two nodes (geographic proximity, social proximity and so forth.). The second approach gives priority to the ratio of benefits/costs, comfort/discomfort, maximization/minimization, etc. Perhaps the most fundamental axiom in social network research is that a node's position in a network determines the opportunities and constraints that it encounters. Network thinking focuses on the fact that the return on investment in human capital (knowledge, skills, abilities) depends to a great extent on the social capital (network position).

Finally, there are two fundamental metaphors that underlie the analysis of social networks. These are the Flow Model and Architecture Model.

According to the first model, the social network is a system of channels (or roads) through which things (information, resources, material and spiritual values) flow. According to the second model, the network makes some skeletons, upon which socio-cultural systems are draped. Any of metaphors reflects the vital function of social analysis to contemporary reality.

Today underestimation importance of network analysis in decision-making leads to serious consequences. From network point of view the result of decision making should be evaluated in context of network changes. Thus great achievements might be a "Pyrrhic Victory", if the environment (eco-environment) becomes less favourable for the leader.

Thus, from traditional point of view Russia wins in the conflict Russia-Ukraine. Ukraine loses resources, territory, doesn't have many strategic resources (gas, oil, nuclear weapons). However, if we take into account the position of the countries in the world network and environment transformation, this conclusion is controversial. Russia has lost influential positions in the world network, Ukraine instead has gained them. Ukraine has rallied the world and mobilized many international forces. It occupied the position of the bridge between the West and the East. Perhaps soon network-politics will replace geopolitics. This conflict should reveal that the world of the twenty-first century differs fundamentally from the world of the twentieth century. From now network position is more significant than territory and resources. Perhaps soon the main indicators of country's power should be network location and network structure instead of GDP. Underestimation of this factor has demonstrated that many of Putin's plans were not implemented, despite the apparent superiority in power.

5 Closing observations

Network analysis has become a point of growth for the social sciences. By making "visible" those that was "invisible", researchers moved forward in understanding of many complex social phenomena (social order, collective behavior, leadership, etc.). By the 1980's, social network analysis had become an recognized field within the social sciences, with a professional organization (INSNA), an annual conference (SUNBELT), specialized software (e.g., UCINET) and its own journal (Social Networks) (Borgatti, et al., 2009, p. 7). Today social network analysis has developed a lot of software packages (e.g. Gephi, NodeXL, UCINet, Pajek, NetworkX, SoNIA).

At the same time, social networks studies has showed some significant differences in research approaches of physicists and sociologists. To be more exact, physicists seek to establish universal laws while the sociologists try to reveal differences. Further, physicists are focused on network structure while social scientists are more interested in the consequences of the network structure (behavior, uniformity, etc.). Sociologists usually concentrate attention at individual nodes, not at the whole network. Finally, sociologists pay special attention to diversities of links while physics tend to generalize regularities.

Differences in perspectives of research, on the one hand, are a prerequisite for the emergence of innovation in this area. On the other hand, the realization of the potential of interdisciplinary interaction depends on the ability of researchers to work at a higher level of complexity, combining not only the knowledge in individual areas but also creating a new way of thinking.

References

1. Albert, R. & Barabasi, A.-L., 2002. Statistical mechanics of complex networks. Rev. Mod. Phys., Issue 74.
2. Barabasi, A.-L., 2014. Network science, `http://barabasi.com/networksciencebook/content/book/_chapter/_3.pdf`
3. Barabasi, A.-L. & Albert, R., 1999. Emergence of Scaling in Random Networks. Science, vol. 286(15), p. 509–512.
4. Barabasi, A.-L., 2014. Network Science, s.l.: s.n.
5. Bollobas, B., 1981. Diameter of Random Graphs. Trans. Am. Math. Soc.
6. Borgatti, S., Mehra, A., Brass, D. & Labianca, G., 2009. Network Analysis in the Social Sciences. Science, 323(5916, Feb 13), p. 892–895.
7. Burt, R. S., 1992. Structural Holes: The Social Structure of Competition. Cambridge: MA: Harvard University Press.
8. Chung, F. & Lu, L., 2002. The Average Distances in Random Graphs with Given Expected Degrees. Proceedings of the Sciences, vol. 99, p. 15879–15882.
9. Coleman, J., 1988. Social Capital in the Creation of Human Capital. American Journal of Sociology , Issue Supplement 94, p. S95–S120.
10. Coleman, J. S., 1988. Social Capital in the Creation of Human Capital. American Journal of Sociology, Issue 94, p. S95–S120.

11. Easley, D. & Kleinberg, J., 2010. Cascading Behavior in Networks. In: Networks, Crowds, and Markets: Reasoning about a Highly Connected World. Cambridge: Cambridge University Press, p. 563–609.
12. Erdös, P. & Rényi, A., 1959. On random graphs. Publ. Math. Debrecen, vol. 6, p. 290–297.
13. Granovetter, M., 1985. Economic Action and Social Structure: The Problem of Embeddedness. American Journal of Sociology, 91(3), p. 481–510.
14. Granovetter, M. S., 1973. The Strength of Weak Ties. The American Journal of Sociology, 78(6), p. 1360–1380.
15. Jackson, M., 2008. Average Distance, Diameter, and Clustering in Social Networks with Homophily. Proceedings of the Workshop in Internet and Network Economics.
16. Jackson, M., 2008. Social and Economic Networks. NJ: Princeton Univ. Press.
17. Judd, S., Kearns, M. & Vorobeychik, Y., 2010. Behavioral Dynamics and Influence in Networked Coloring and Consensus. Proceedings of the National Academy of Sciences, 107(24), p. 14978–14982.
18. Kearns, M., Judd, S., Tan, J. & Wortman, J., 2009. Behavioral experiments in biased voting in networks. Proceedings of the National Academy of Sciences, 106(5), p. 1347–1352.
19. Krebs, V., 2000. The Social Life of Routers. The Internet Protocol Journal, vol. 3(4), p. 13–25.
20. Krebs, V., June 2000. Working in the Connected World. IHRIM Journal, p. 89–90.
21. Lorrain, F. & White, H., 1971. Structural equivalence of individuals in social networks. Journal of Mathematical Sociology, p. 67–80.
22. Milgram, S., 1967. The Small-World Problem. Psychology Today, Issue 2, p. 60–67.
23. Newman, M., 2003. The structure and function of complex networks. SIAM Rev., vol. 45, p. 167–256.
24. Pugacheva, E., 2003. Searching the Way of Scientific Dialogue and Understanding. Interview with Prof. H. Haken (in Russian). Higher Education in Russia, Issue 4, p. 96–100.
25. Sayama, H., 2015. Introduction to the Modeling and Analysis of Complex Systems. State University of New York at Geneseo: Open SUNY Textbooks, Milne Library.
26. Uzzi, B., 1996. The Sources and Consequences of Embeddedness for the Economic Performance of Organizations: The Network Effect. American Sociological Review, vol. 61, p. 674–698.
27. Watts, D. & Strogatz, S., 1998. Collective Dynamics of 'Small-World' Networks. Nature, pp. 393-440.
28. Watts, D. & Strogatz, S., 1998. Collective Dynamics of 'Small-World' Networks. Nature, vol. 393, p. 440–442.