DE GRUYTER
OPEN

DOI: 10.1515/irsr-2013-0019

IRSR INTERNATIONAL REVIEW of SOCIAL RESEARCH

Volume 3, Issue 3, October 2013, 21-38 International Review of Social Research

Is the Positive Network the Inverse of Negative Network?

Balázs TELEGDY•

Sapientia - Hungarian University of Transylvania
Faculty of Technical and Social Sciences
Department of Social Sciences

Abstract: The aim of this study is to identify the central and peripheral actors in two ethnically homogenous theoretical high school classes, in order to prove that the positive and the negative ties produce different networks. Measures of density and centrality were used for identifying differences between the two types of social networks. The results confirmed that, at the network level, the negative network is not the inverse of the positive network. At the individual level, results did not indicate whether those persons who are on the periphery of the positive network are also on the periphery of the negative network. Furthermore, besides confirming the fact that the positive networks are denser than the negative ones, I found that negative networks are highly polarized in comparison with positive networks.

Keywords: *centrality and density measures, high school classes, negative and positive networks, social network analysis, Ucinet 6.*

Introduction

The characterization of negative network by revealing their differences from the positive social networks is a relative new field of research. In the field there were several attempts to describe the characteristics of the negative networks using multiple approaches, like the negative relationship for calculating one actor's status (Bonacich and Lloyd, 2004), or negative relationship for explaining several social phenomena usually labeled as negative, such as bullying (Huitsings et al., 2012; Tolsma et al., 2013), group conflict (Labianca et al., 1998; Neal, 2009), or gossip (Ellwart, Steglich and Wittek, 2012; Ellwart, Labianca and Wittek, 2012), while positive network analyses are used to uncover different illegal consumption habits (Henry and Kobus, 2007; Mercken et al., 2010, Kreager and Haynie, 2011).

The affinity towards a similar

•e-mail: telegdybalazs@sapientia.siculorum.ro. Balázs Telegdy currently works as an Assistant Professor of Social Sciences, at Sapientia Hungarian University of Transylvania (Romania). He received his MA in Sociology from "Babeş-Bolyai University" in Cluj-Napoca with an analysis of the regional disparities of the social problems in Romania, and currently he is writing PhD thesis on the history of Romanian sociology at the University of Bucharest. His other research interests include the sociology of transition, institutional trust and social network analysis.

person, which materializes in associations, is a well known characteristic of the social networks (Lazarsfeld and Merton 1954). Both macro and micro levels are affected by the implication of homophily. Given the fact that I have analyzed a well-defined group of people, my current study focuses only on the micro level characteristics of the phenomenon.

The other classification of the scholarly explanations of homophily can be divided by two inducements: the preference-based and the structural-based approaches. My analysis follows the structural approach, as I intend to prove that the positive and negative networks have different internal structures.

My study investigates the structural relation between the positive and negative networks, in order to identify the differences and similarities in both types of networks and actors.

Theory and Hypotheses

The positive and the negative ties

As an introduction regarding the positive ties I would like to start with the notion of homophily. The analysis of the positive and negative relationships dates back to Heider's structural balance theory, as this explains the existence of a relatively stabile social arrangement between the actors using the classical p-o-x approach which already contains positive and negative connections (Heider, 1948). The application of the presented model on social groups (Newcomb, 1961; Cartwright and Harary, 1958), generalizing its explanatory power, concluded in major consequences: it created the possibility to apply the social balance theory on groups and their network dynamics, and also made the positive and negative relationships possible to analyze. On the basis of Burt's (Burt, 1990) approach, who argued, that persons with similar statuses and role sets are more likely to close a friendship. Furthermore, Blau, cited by Moody (Moody, 2001:9) argues that the people who meet very often are more likely to create a friendship. Based on this, I can assume that in case of a high school class, where the students meet regularly on daily basis, the accepted, pro-social relationship should be mutual friendship.

Even if the negative relationship dates back to the early origin of network analysis, only the last decade focuses explicitly on the particularities of the negative network. Multiple researches have shown that the analysis of the negative group ties is an important aspect of the social organizations (Labianca, Brass and Gray, 1998:63), as they are a necessary accompanier of the closed social network (Labianca and Brass, 2006:2). This approach is based on the structural balance theory, which supposes the simultaneous existence of positive and negative ties.

Furthermore, as it was proven by previous studies, the effect of negative ties can cause dysfunctions within an organization, as informal ties have a clear effect on formal ties. Theoretically, in high schools, the formal position of each student should be equal, while the informal positions in both positive and negative networks are differentiated, and, as a conclusion, it affects the formal function of the educational institutions. To argue this perspective is enough to mention those studies which detect different deviant behavior or consumption among students, like bullying (Huitsing et. al., 2012, Tolsma et al., 2013), drinking (Kreager, 2011) or smoking (Mercken et al., 2010). From this perspective I consider the identification of both positive and negative networks important, as these are relatively independent from the formal network.

Parallel identification of the positive and negative relations in a network has a methodological significance, as the absence of the positive connection in the positive network does not automatically mean that there is a negative relationship, it could be also a neutral one (Huitsing et al., 2012:646). For this reason, the simultaneous measurement of both types of relations between the members of the analyzed groups seems to be a must for a correct measurement.

The analysis of the positive relations and ties by themselves constitutes the bulk of the social network based analyses, which is understandable, in comparison with the negative relations analysis: the previous researches proved that the structure of positive networks is much denser and the number of ties is much higher than in case of negative networks, and so it is much easier to model, and to test significant hypothesis. On the other hand, it is much acceptable to ask people about their positive relations than to ask inconvenient questions about one's dislike or antipathy toward one's colleagues.

At this point a conceptual distinction should be made between the concepts of ties and relations. According to Prell (2012), while the concept of ties refers to the existence of a connecting relation, as one actor is tied to an other actor, the term of relation means 'a specified set of ties among a set of actors' (Prell 2012: 9).

In my study, by negative tie I understand a generalized dislike and antipathy toward one's classmates, while by positive tie I refer to a generalized like or sympathy. As a conclusion, the negative network consists in the directional ties of the negative relationships within a class, while the positive network means the directional ties of the positive relationships within a class.

Basing on the previous research, I have assumed that the positive and negative social networks are not their own mirror images (Csaba and Pál, 2010). Taking the network analysis down to personal level, I added the assumption that the people on the periphery of the positive network would play a central role in negative network, the same also being true for the inverted situation.

The measures of centrality

Similarly in both positive and negative cases, the centrality measures are used to identify the key players in these types of social networks. In my research I used directional measures to compare the positive and negative centrality.

The idea of using multiple centrality measures in my analysis is based on the findings of Gomez, González-Arangüena, Manuel, Owen, del Pozo, Tejada (2003), according to whom 'the multiplicity and diversity of formal definitions proposed for centrality measures indicate that there is not a unique type of centrality and that different problems must give rise to different measures.' (Gomez et al., 2003: 52). Out of this consideration, for a proper comparison of the positive and negative network, I decided to analyze the following centrality indicators: degree centrality, betweenness and closeness.

The main centrality indicators I used in my analysis were the indicators relevant for directional measures provided by the statistical package of UCINET 6. To point out the potential differences between the positive and negative networks, I used several centrality indicators in order to get a wilder basis for the comparison. According to Freeman (1979:219) the centrality of a point in a graph could be determined from three different aspects: the degree, the betweenness and closeness. As a consequence, I took into account the following indicators: degree centrality, betweenness centrality and closeness centrality.

The degree centrality is the most widely used centrality measure, mainly because it is 'the simplest and most straightforward of the centrality indices' (Zemljič and Hlebec, 2005: 75). This indicator shows the number of a person's connections in a directional, non-symmetrical network. Practically each person's centrality indicates the number of connections or ties possessed by the actor in the network (Freeman, 1979: 220-221). The higher the value is, the higher the number of ties possessed by the actor would be, so the actor with the highest number of degree centrality is the most popular in the positive networks, and the most unpopular in the negative networks. In the case of non-symmetric analysis, there are two different types of degree centrality measures: the in-degree, which represents the number of choices received by an actor, and the out-degree which represents the number of choices made by an actor.

Using the Freeman's degree centrality as a starting point, Bonacich expanded the explanatory power of this type of centrality by adding importance to the connections by the actors. This approach gains a particular importance when two ore more actors have the same number of connections, which apparently makes them equally powerful within the network. But the application of Bonacich's Power Index creates a qualitative distinction among actors, taking into consideration the centrality of the other actors with whom he/she is connected. From this perspective, it is not necessary for an actor to possess the highest degree centrality in order to be the most powerful actor in a network. It is enough to be in connection with the other powerful actors.

Another indicator which represents a point's central position in a network is the betweenness meaning that an actor occupies a strategic position in the network, so the information between two or more actors must pass through it (Freeman, 1979: 221). This indicator plays an important role in the network, as it identifies the actor considered the leader of a specific group or network (Freeman, 1980: 128). Practically, the betweenness, as an indicator, represents the potential or the possibility of controlling the information in a certain network.

The third indicator used by me to identify the central actors in the two different networks is the closeness. This indicator practically shows the independence of an actor form the other actors not directly connected to her/him, as its lowest value represents the central point in a network (Freeman, 1979: 225). As this indicator is also applicable for non-symmetric measures, I am making a difference between in-closeness, which represents the shortest geodesic distance received by an actor, and the out-closeness which represents the shortest geodesic distance made by the actor.

The measures of density

Beside the centrality measures, the network analysis also calculates different types of statistical indicators which describe the network's holistic characteristics. In order to verify the differences between the positive and negative networks in the two classes, I used the centrality measures applied in descriptive statistics as well. The indicators I used are the mean, and the standard deviation in the cases of the different centrality measures presented above. As measures of density the value of mean will help me to identify the differences between the positive and negative networks, as it represents the percent of all existing ties in comparison with the number of all possible ties. As the number of actors is the same in the class, both in the positive and the negative networks, the value of mean is one of the main indicators which can prove the similarities or the differences within the class in these types of networks. A second indicator will be the value of the standard deviation, which reveals the overall directions of the positive and negative relationships. Furthermore, the standard deviation value gets an extra explanatory power when it is compared with the value of mean, as their ratio reveals the polarization of the different types of networks within a class.

The particularities of the high school classes

The high school classes are a special ground for network analysis because they have several controllable characteristics. First of all, the size of a class is a very important characteristic, as the students from high school class constitute a close community, with a relatively constant number of participants. As a consequence, the relationships among them are more or less personal, so every participant of the group has a personal opinion regarding its relationship with her/his classmates, as it is usual in micro-level groups. In the same time, these classes are populous enough to divide in cliques, so they reach the critical mass to create, beside positive connections, negative connections as well. Thus, this type of groups represents an ideal field for research form many perspectives, as it creates a consistent social context for social network analysis. Furthermore, as high school classes are an important reference group for their members, beyond the social network aspect, the sociological aspect could also have an important explanatory value.

Hypotheses

Resuming the presented pioneering findings of Bonacich and Lloyd (2004), also tested by Csaba and Pál (2010), my main hypothesis is that the positive and negative networks are not each other's inverse (H1). Going further, if the positive network and the negative network would be each other's inverse image, than the QAP correlation would have a -1 value, meaning that within a class negative ties would be only where positive ties do not exist and vice versa. Reflecting on the individual level, my further hypothesis is that those persons who are on the periphery of the positive network will be on the periphery of the negative network as well (H2). This assumption is based on the idea that a person who is not appreciated positively within a class it does not necessarily has to be a core actor in the negative network. Reversing this statement also can not be assumed that a student who is not a core actor in the negative network will be popular in the positive network.

Data Measurements and Methodology

Data

In order to test my hypotheses I used a self-administrated questionnaire which I thought to be suitable for the collection of this type of data, observing its sensible and personal character. The field of research comprised two 10th grade classes school from a Sfântu Gheorghe theoretical high school. I choose these classes taking into account two aspects. Firstly, as the high school starts in Romania with the 9th grade, I assumed that the students had plenty of time to get to know each other and to form a personal connection which each others. Secondly, I chose a school having a single teaching language, to reduce the most powerful effect which creates segregation in the school classes, namely the ethnicity and race of the students (Moody, 2001: 680), in some cases completed by gender (Kreager and Staff, 2009: 155) which could manifest in bullying (Tolsma, van Deuzen, Stark and Veenstra, 2013).

Measures

In my analysis I used the quantitative methodology to verify the hypotheses. Accordingly, I collected data form the analyzed population using a standardized questionnaire, competed by all the students from the two selected classes. Beside the classical demographical and socio-economic questions (regarding the sex, age, domicile, religion, ethnicity, the parents' marital status, the parents' occupation, the parents' educational level and the subjective appreciation of the comparative wealth level), I also asked information about their performance in school (the grade point average), about the facultative, but regular activities both in and outside the school, the frequency of consuming the following products: energy drink, coffee, alcohol, cigarette and tea. The questionnaire also contained questions about the students' preferred music and about their love life, asking whether they have/had a partner.

In order to determine the 'interpersonal affective network' (Labianca et al., 1998: 60), I used a five degree Likert scale, and the students were asked to determine their relationship with their classmates. Expanding the classical approach of Heider (1958), based on 'friend' and 'enemy', the five categories were: 1. my friend; 2. rather sympathetic classmate; 3. neutral; 4. rather antipathetic classmate and 5. my enemy. In order to determine the characteristics of the two types of networks – the positive and the negative – I decided to apply the data collection in two classes, in order to be able to compare the results for a higher level of confidence. The sizes of the two classes were: Class X had 31 students and Class Y had 27 students. The questionnaires were applied in the classrooms, in a single wave in Class X, and in two waves, because of several absent students, in Class Y. The data collections were conducted in April 2013, during the week of 'Şcoala altfel' (School differently).

To ensure the best data collection method I choose to apply a self-administrated questionnaire, which grants the student the autonomy and also the intimacy essential in naming the classmates in both positive and negative relationship. The positive and negative relationship was indicated on a matrix, where the columns signaled the quality of relationship, while each row contained the name of a student from the class in alphabetical order. The students were instructed to mark with a small dot their own names, in order to grant the directional character of the relationship. Following this methodology, I applied this questionnaire to all the participants in the two selected classes, giving the aggregate number of n = 58 students.

Finally, my results show a cross-sectional view of the two classes' networks, as the data collection was conducted only once in the selected classes.

The identities of the students are covered by numbers which were randomly associated to them in order to assure the total anonymity of the participants.

Analyses and results

In order to test my hypotheses in the first step I have calculated, with the help of the UCINET 6 software, the centrality indicators for the two types of networks, in both classes. As the 'friend', 'sympathetic', 'neutral', 'antipathetic' and 'enemy' notions used were not defined, I took only the direction of the emotion toward the classmates into consideration, so by the positive network I mean the aggregate value of the 'friends' and 'sympathetic' classmates, and by the negative network I mean the aggregate value of 'antipathetic' and 'enemy' classmates. The 'neutral' values were left out of the current analysis; based on the assumption that in the context of the positive and negative feelings these do not convey any emotion toward the classmates.

In order to test the statistical reliability of my computed indicators, I applied the Cronbach's Alpha test to analyze the internal consistency. In all four cases – the two types of networks in the two analyzed classes – the value of Cronbach's Alpha reached the statistical acceptance level. Its lowest value was, in the case of positive networks in Class Y (0.656), while in the case of negative network in the same class was 0.791. In the Class X this value was 0.817 in the positive network and 0.841 in the negative network. As a conclusion, my scale proved to be adequate for a statistically reliable analysis.

In the positive and negative matrixes created separately for each class the student's choices were coded as dichotomies: the nulls represent the lack of choice, and the ones represent the directional choice made by the students towards their classmates in both types of networks. This approach is methodologically indicated as well, as the majority of the centrality and density indicators used by me have an explanatory value only under these conditions.

For the analysis, I used an asymmetric network (Labianca et al., 1998; Bonacich and Lloyd, 2004) and also the findings of Csaba and Pál (2010), according to whom among high school student is common that they do not mutually consider each other 'friends' or 'enemies' (Csaba and Pál, 2010: 78).

As the graphic presentation shown in Figures 1 and 2, the difference between the two types of networks is obvious at first sight, in the case of both classes.

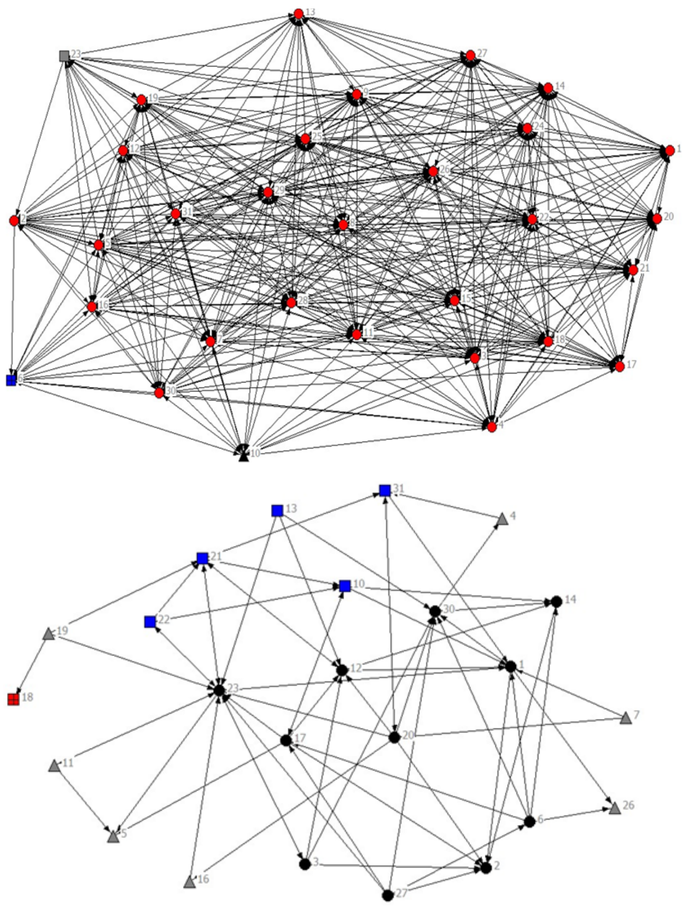

Figure 1. The k-core results of the positive (up) and negative (down) social network of Class X. Positive network: circle 19, square 17, up triangle 16, box 15; negative network: circle 4, square 3, up triangle 2, box 1, down triangle 0.

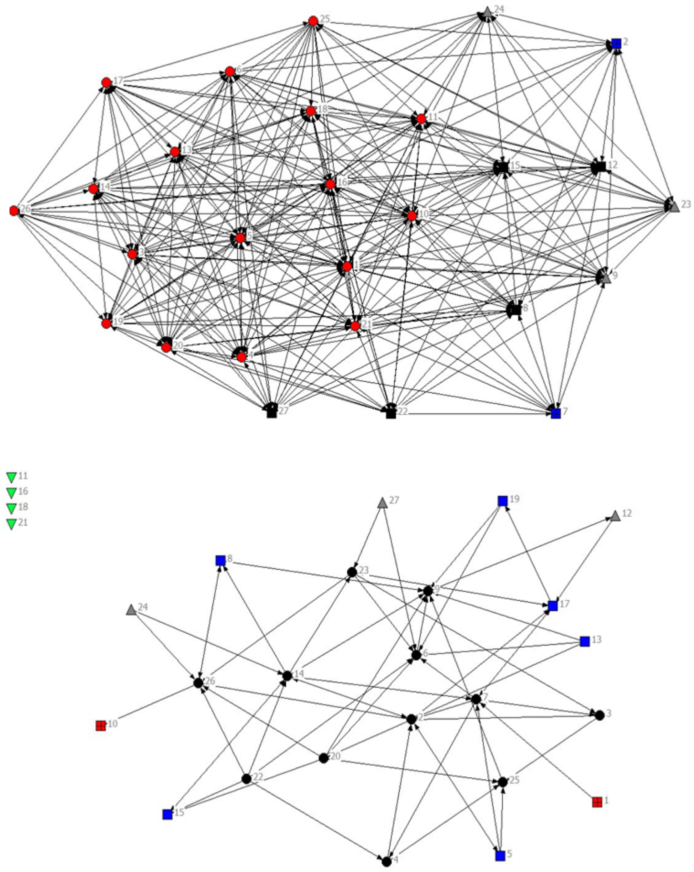

Figure 2. The k-core results of the positive (up) and negative (down) social network of Class Y. Positive network: circle 14, square 13, up triangle 12, box 11; negative network: circle 4, square 3, up triangle 2, box 1, down triangle 0

Density measures

The first sets of indicators used to test my basic hypothesis were the density measures, calculated for both classes for the positive and the negative network. As in the hypothesis I made a statement referring to the whole network, when I calculated the density indicators I applied the measurement for the whole matrix, not only for the indegree or for the outdegree. Also I decided to use the mean and standard deviation in this research, not only because their powerful explanatory value, but also because their values can be compared even if the number of analyzed cases in the two classes is not equal.

The value of the means is explicitly expressing a network's density, as when all the possible connections exist it would reach the value 1 (= 100 per cent), or, on the contrary, the total absence of the possible connection within the matrix would result 0 (0 per cent). In this analysis, even if there are some differences between class X and class Y, it can be concluded that the positive networks are much denser – 62.4 per cent, respectively 53.8 per cent – then the negative ones – 7.4 per cent, respectively 8.7 per cent. These results have a confirmatory aspect, as previous researches also came up with the same findings. (Labianca and Brass, 2006; Csaba and Pál, 2010)

The value of standard deviation gains importance when we compare its value to the mean. In case of both classes the value of standard deviation approaches the value of the mean without exceeding it (see Table 1). This result means that there is a polarization among the students of both classes, so we can easily locate the leaders and the ones on the periphery too, as it is shown in the graphs for the two classes' positive networks.

Table 1. *Density indicators for both positive and negative networks in Class X and Class Y*

Density indicators	Class X		Class Y	
	Positive network	Negative network	Positive network	Negative network
Mean	0.624	0.074	0.538	0.087
Standard deviation	0.484	0.262	0.499	0.282

In the case of negative networks, the situation is much clearer. As the standard deviation in both classes shows an extremely high value in comparison with the means – more than three times bigger in both cases – it expresses a powerful polarization in the two classes analyzed (as shown in Table 1).

Using the hypothesis testing feature in UCINET6 program I compared the positive and negative ties within the two classes, with the QAP correlation. The results in both cases show a significant difference (in Class X $r = -0.356$, $p<0.000$ and in Class Y $r = -0.333$, $p<0.000$). The values of Pearson's correlation in each case suggest that the positive and negative networks are not each others mirror images, as the value of these indicators is far less then -1, which should mean the total opposition. Beside this statement, the negative correlation reveals the fact that in general, the actors who have more positive connections also tend to have less negative ones.

As an initial conclusion, I can assume that the density indicators prove my first hypothesis, that the positive and negative networks are not each other's inverses. Furthermore, besides confirming the fact that the positive networks are denser than the negative ones; I found that negative networks are highly polarized in comparison with positive networks.

Centrality indicators

After the use of density measures to test the first hypothesis, I calculated the main centrality indicators in order to confirm, from this perspective as well, the findings regarding the positive and negative networks, but also the person's situations within these networks.

First I compared the centrality measures for the two types of networks, for both classes (see Table 2).

Table 2. *Centrality indicators for both positive and negative networks in Class X and Class Y**

Centrality indicators	Class X		Class Y	
	Positive network	Negative network	Positive network	Negative network
Degree centrality (outdegree mean)	18.71	2.23	14	2.26
Degree centrality (outdegree standard deviation)	5.41	2.03	3.8	1.84
Degree centrality (indegree mean)	18.71	2.23	14	2.26
Degree centrality (indegree standard deviation)	4.71	2.06	4.88	2.35
Network centralization (outdegree)	33.10%	13.45%	49.85%	15.54%
Network centralization (indegree)	22.41%	31.26%	33.23%	19.69%
Betweenness (mean)	11.32	18.13	12.15	26.85
Betweenness (standard deviation)	7.73	28.86	8.33	38.41
Network centralization index (betweenness)	2.36%	12.9%	3.53%	14.81%
Closeness centrality (outcloseness mean)	73.88	11.83	69	13.55
Closeness centrality (outcloseness standard deviation)	9.81	3.21	8.22	2.58
Closeness centrality (incloseness mean)	73.49	15.54	69.35	22.05
Closeness centrality (incloseness standard deviation)	7.73	6.78	8.97	9.90
Network out-centralization	41.77%	-	65.68%	-
Network in-centralization	25.71%	-	36.69%	-

**See the note placed at the end of the paper*

As in the case of the network density measures, the centrality indicators show explicitly the differences between the two types of networks in both classes.

The Freeman degree of centrality reveals the fact that in both classes the number of the positive appreciations was much higher than for the negative ones – 8.4 times more in the case of Class X and 6.2 times more in the case of Class Y. The standard deviation in both classes shows in the negative network a value close to the mean, which also represents a higher level of polarization in comparison with positive networks. These results confirm the findings of Labianca and Brass (2006), according to whom the people are generally seeking the positive relationship instead of the negative, conflict-based relationship (Labianca and Brass, 2006: 597).

The network centralizations based on indegree and outdegree also present similar scenarios in both classes, even if the particular values show some differences. In the positive network the indegree network centralization value is higher than the outdegree network centralization – more than 10 per cent in each cases –, which means that the amount of positive connections marked by the students disperses to several other students. In contrary, in the case of negative networks, the indegree network centralization value is higher than the outdegree network centralization – more than double in the case of Class X, and just 5 per cent higher in Class Y –, which reveals the fact that the fewer connections mentioned are well oriented towards a few receivers.

The second type of centrality measure used was the betweenness centrality. The results, as in previous cases, reveal a higher level of concentration towards several particular students. In both classes, the value of the mean and the standard deviation of betweenness are higher in negative networks. Comparing the values of the mean and the standard deviation indicates also similarities of the classes, as, regarding the positive network, the value of the means are higher than the standard deviation, representing a smaller variation in the betweenness of each actor. The negative networks present opposite scenarios: the values of the standard deviation are higher than the mean, pointing to a high level of variation within the networks.

The network centralization index of betweenness is rather low in each case, adding the remark that the negative networks' values overpass the positive ones. This result is interpretable in the structural context, as the betweenness according to Freeman's approach loses a lot of its power, due to the fact that the majority of connections are direct, so they do not need intermediary actors. Even though, the negative networks resulted a higher level of betweenness, meaning that fewer students are in central position in comparison with the positive network.

The third applied indicator set was the closeness, based on Freeman's approach of geodesic paths. Once again, the mean values are much higher in the case of positive networks that in negative ones, revealing that the students occupying a more central position in the negative network receive more direct votes. If we compare the mean values of incloseness and outcloseness, the relative equality of positive networks is in contrast with the values of negative networks. The higher value of the outcloseness mean in both classes reveals that the students declaring negative connections towards their classmates are more distanced from each other then the students who receive negative appreciations.

The second hypothesis concerned the different actors' centrality, as I supposed that those students who are on the periphery of the positive network will also be on the periphery of the negative network as well.

To test this statement, I calculated the above mentioned centrality indicators, as they are actor based indicators, for both types of network and for both classes. Also I was interested in indicating the central and peripheral actors by the positive or negative marks of their classmates, which firstly means that I used asymmetrical measures that indicate the direction of choices and secondly with the use of the centrality indicators I tested the hypothesis only with the indegree results, excepting betweenness. In Table 3, the three most central and the three most peripheral students are presented. In cases when there is equality in the central measures score, the table contains more than three individuals in a given cell.

Table 3. *The list of the students in the central or peripheral positions, within the networks in both classes*

Centrality indicators	Class X				Class Y			
	Positive network		Negative network		Positive network		Negative network	
	Central	Periph.	Central	Periph.	Central	Periph.	Central	Periph.
Indegree centrality	25, 15, 22	23, 4, 5	23, 12, 30	7, 8, 9, 13, 15, 19, 24, 25, 27, 28, 29	5, 11, 1, 20	7, 25, 26	6, 9, 2, 26	1, 11, 13, 16, 18, 21, 22, 24, 27
Indegree Bonacich's Power Index	22, 15, 25	23, 5, 10	23, 12, 1	7, 8, 9, 13, 15, 19, 24, 25, 27, 28, 29	5, 1, 20	25, 7, 26	9, 17, 2	1, 11, 13, 16, 18, 21, 22, 24, 27
Between centrality	8, 29, 28	23, 1, 6	23, 1, 21	5, 7, 8, 9, 11, 13, 15, 16, 18, 19, 24, 25, 26, 27, 28, 29	10, 11, 1	26, 27, 7	17, 7, 9	1, 10, 11, 13, 16, 18, 21, 22, 24, 27
Incloseness centrality	25, 15, 22	23, 4, 5, 10	5, 26, 23	8, 9, 15, 24, 25, 28, 29	5, 11, 1, 20	25, 26, 7	9, 17, 10	11, 16, 18, 21

The results infirm the starting presumption, as some of the students who are on the periphery of the positive network occupy a central position in the negative network. This is the case of the student # 23 in Class X, according to all centrality measures used, and student #1 in the betweenness centrality. In the case of Class Y the students #7 and #26 are the ones which appear to be in central position in a negative network, simultaneously being in a peripheral position in the positive network.

In the opposite cases, those students which are in central positions according to the applied measures show a higher degree of superimposition with the negative network peripheral positions. For example, the students #15 and #25, which are in central position in Class X are in peripheral position according to the same indicators in the negative network.

Groups and subgroups

In order to test the validity of the above presented result regarding the positions of the different actors within the positive and negative networks, beside the individual level approach, I completed my analysis with grouping methods which can reveal the structural equivalency of the different players, based on their participations in the larger sub-groups existent in the classroom. As I intend to identify the core and the peripheral actors in both positive and negative network in the two analyzed class, I will use a top-down approach, which is suitable for my research.

According to the results of the k-core analysis, the actors' membership in sub-groups with different density level can be compared with the individual level degree-based positions. In the case of class X, the core group of the positive network, who has the highest value (19) dominates almost the totality of the class, as only three actors are situated on the periphery, participating in less subgroups. These actors are #23, #10 and #6. On the other hand, in the case of negative network, the periphery consists of those actors who did not get any negative nominalizations. Regarding the issue of the central and peripheral actors in these two types of networks can be stated that while the peripheral actors of the negative network are in the core of the positive network, the peripheral actors of positive network are in central positions – beside other actors – in the negative network.

In the case of class Y, where the relationships are more dispersed, the core group consists in a smaller group of students than in class X. As a consequence, I will consider peripheral the actors #2 and #7, who reached the lowest level in the k-core analysis. Regarding their presence in the negative network, they are occupying – along with 10 other actors – the central positions. The peripheral actors in this negative network, which possess no negative tie within the class, are the actors #11, #16, #18 and #21, who are in the central core of the positive network, along with other 13 classmates.

After proving the significant differences between the two types of networks I analyzed the structural differences between the networks in order to identify the core and peripheral actors in the presented classes. For this reason I applied the Core/Periphery algorithm built in the UCINET 6 program. After identifying the core and the peripheral groups in each type of network in both classes, I tested the statistical significance of the membership between the core and the periphery, both in the case of the positive and the negative network. Coding each actor's presence in a subgroup as a dummy variable, 0 meaning not member, 1 meaning member of the subgroup, and aggregating the results of the two classes I conducted the chi-square analysis, which led to the following results: the value of chi-square was 4.4 (df=1, significance $p=0.036$) when I compared the core actors in the positive and in the negative networks. This result reveals that an actor who is in core position in the positive networks has a significant chance of being in the core of the negative group. Assuming the interdependence of the positive and the negative networks, and, in conclusion applying an asymmetric measure to identify the power of the connection between the two groups, I conducted the lambda test. In this case the value was $\lambda=0.263$, with an approximate significance of $p=0.088$. These results reveal that the influence of the interconnection between the memberships of the two core groups in the two types of networks is not statistically significant. Regarding the connection between the core positive and peripheral negative subgroups, the values of chi square and lambda were similar (as the membership of the core group automatically presumes the lack of presence in the peripheral group and vice versa) but the value of the significance level of the lambda decreased (to $p=0.112$).

Regarding the dichotomous character of the core-periphery membership of the actors in the negative networks as well, the presented results are similar in the comparison of peripheral membership in the positive network with the core and the peripheral subgroups.

As a partial conclusion, it can be stated, from the structural perspective, that the chance of a core actor in the positive network being among the core actors of the negative network is significant, but the predictor value is rather low. This affirmation is confirmed by the Goodman and Kruskal tau and the Uncertainty Indicators, which are both statistically significant ($p< 0.5$ in both cases), but have low values (0.076, respectively 0.056).

These two cases led the conclusion that the position occupied by an actor within a positive network does not explain its position in the negative network. The reverse of this statement is also true.

Discussion and Conclusions

Through my analysis I identified the actors' positions in two high school classes in both the positive and the negative networks in order to prove that positive and negative networks are not each others mirror images, in the sense that these two networks are not each others inverse. Based on density, centrality and grouping indicators, my first hypothesis was confirmed.

My second hypothesis was partially drawn from the first one, namely that those persons who are on the periphery of the positive network will also be on the periphery of the negative network as well.

The confirmation of the second hypothesis was conducted in two steps. At first, I analyzed it from the structural perspective. After identifying the core and peripheral groups in the positive and negative networks of both classes, I compared the selected groups' memberships. The results show that there is a significant, but weak interconnection between the different groups' memberships, as the presence in the core group of the positive network influences positively the presence on the periphery of the negative network. According to the dichotomous character of the memberships of the presented subgroups, this conclusion is valid for the other comparison as well. As it follows, the presence in the core group of the positive network influences negatively the presence in the core group of the negative network. Similarly, the membership in the peripheral group of the positive network increases significantly the presence in the core of the negative network, and decreases significantly the presence in the periphery of the negative network.

At individual level, the differences between the two types of networks produced different levels of central - periphery positions, so the peripheral actors in negative networks are far more numerous that in the case of positive networks. This led to the conclusion that being in central position in positive networks is not the only explanatory factor of being in peripheral position in the negative network. Secondly, while in the case of Class X one actor plays a central role in the negative network and peripheral in the positive one, in the case of all centrality measures applied in my research; in the case of Class Y this domination by an actor was not observable.

These results can be interpreted hypothetically in the following ways: firstly, as the densities of the positive networks are much higher then those of the negative ones; the possibility of selection in a positive connection is also much higher in comparison with a negative connection. Also it seems plausible that those students, which are able to gain the sympathy of their classmates, also have the ability to cope positively with their interpersonal conflicts. This seems plausible as Bryson's 'educated tolerance' has no effect in this particular case (Bryson, 1996: 895), as each person in my analysis has the same level of education. On the other hand, following Neal's results, it can be stated that those who are not on the extremities of the social network are more involved in interclass conflicts (Neal, 2009: 748).

Secondly, applying the homophily approach, it seems that a few actors appear in the central positions of the negative network and on the periphery of the positive one, while others only according to one particular centrality indicator. Analyzing the structural position of the actors in both positive and negative networks it can be concluded that structural equivalence could be based on similarities or on social balance (Moody, 2001: 683-685).

Thirdly, according to Takács (2001: 766) '… [it] predicts a strong positive effect of segregation if normative pressure is more important than confirmation pressure of neighbors and friends.' From this perspective it can be assumed that while in the positive networks the confirmatory pressure can be more important, in the negative network the cited results are valid. But this is the hypothesis of a new research.

Finally, summing up the findings of the current research can be stated that the presence of an actor in the core of the positive network of a class has a low predictor value regarding the negative network core, or the peripheral subgroups of the same class.

Acknowledgement

I would like to thank for my two anonymous peer-reviewers for their useful comments, which helped me to improve my paper.

Note

Concerning the closeness indicator, two methodological remarks are needed: in order to get real and interpretable results for negative closeness centrality indicators, those students who possess no connection (either in-, nor out-) were left out of the calculation. Secondly, because the negative networks were not closed in the analyzed two classes the network centralization could not be computed.

References

Bonacich P. and P. Lloyd (2004) ‘Calculating status with negative relations’. *Social Networks,* 26(4): 331 - 338.
Bryson, B. (1996) ‘Anything But Heavy Metal: Symbolic Exclusion and Musical Dislikes’. *American Sociological Review,* 61(5): 884 - 899.
Burt, R.S. (1990) ‘Detecting Role Equivalence’. *Social Networks,* 12(1): 83 - 94.
Cartwright, D. and F. Harary (1956) ‘Structural balance: a generalization of Heider’s theory’. *Psychological Review,* 63(5): 277 - 293.
Csaba, Z.L. and J. Pál (2010) ‘How Negative Networks Are Forming and Changing in Time’. *Review of Sociology,* 20(2): 69 - 95.
Ellwart L., G. Labianca, R. Wittek (2012) ‘Who are the objects of positive and negative gossip at work?: A social network perspective on workplace gossip’. *Social Networks,* 34(2): 193 - 205.
Ellwart L., C. Steglich and R. Wittek (2012) ‘The co-evolution of gossip and friendship in workplace social networks’. *Social Networks,* 34(4): 623 - 633.
Freeman, L.C. (1979) ‘Centrality in Social Networks - Conceptual Clarifications’. *Social Networks* 1: 215 - 239.
Gomez, D., E. González-Arangüena, C. Manuel, G. Owen, M. del Pozo and J. Tejada (2003) ‘Centrality and power in social networks: a game theoretic approach’. *Mathematical Social Sciences,* 46(1): 27 - 54.
Heider, F. (1948) ‘Attitudes and Cognitive Organizations’. *The Journal of Psychology,* 21(1): 107-112
Henry D.B. and K. Kotbus (2007) ‘Early Adolescent Social Networks and Substance Use’. *Journal of Early Adolescence,* 27(3): 346-362
Hanneman R.A. and M. Riddle (2005) ‘Introduction to Social Network Methods’, http://faculty.ucr.edu/~hanneman/nettext/Introduction_to_Social_Network_Methds .pdf. (Retrieved: October 12, 2013)
Huitsing, G., M.A.J van Dujin, T.A.B. Snijders, P. Wang, M. Sainio, C. Salmivalli, R. Veenstra (2012) ‘Univariate and multivariate models of positive and negative networks: Liking, disliking, and bully-victim relationships’. *Social Networks,* 34(4): 645-657
Kreager, D.A. and J. Staff (2009) ‘The Sexual Double Standard and Adolescence Peer Acceptance’. *Social Psychology Quarterly,* 72(2): 143 - 164.
Kreager, D.A. and D.L. Haynie (2011) ‘Dangerous Liaisons? Dating and Drinking Diffusion in Adolescent Peer Networks’. *American Sociological Review,* 76(5): 737 - 763.
Labianca, G., D.J. Brass and B. Gray (1998) ‘Social Networks and Perception of Intergroup Conflict: The Role of Negative Relationship and Third Parties’. *Academy of Management Journal,* 41(1): 55 - 67.
Labianca, G. and D.J. Brass (2006) ‘Exploring the Social Ledger: Negative Relationships and Negative Asymmetry is Social Networks in Organizations’. *Academy of Management Review* 31(3): 596 - 614.
Lazarsfeld, P.F. and R.K. Merton (1954) ‘Friendship as a social process: a

substantive and methodological analysis'. In Berger, M. (ed) *Freedom and Control in Modern Society*, pp. 18-66. New York: Van Nostrand

Letenyei, L., and Vedres, B. (2005) 'Kapcsolatháló e-kurzus', http://www.socialnetwork.hu/enetw.htm. (Retrieved: October 20,2013)

Mercken, L., T.A.B. Snijders, C. Steglich, E. Vartiainen and H. de Vries (2010) 'Dynamics of adolescent friendship networks and smoking behavior'. *Social Networks,* 32(1): 72 - 81.

Moody, J. (2001) 'Race, School Integration, and Friendship Segregation in America'. *American Journal of Sociology,* 107(3): 679 - 716.

Neal, J.W. (2009) 'Network ties and mean ties: a relational approach to relational aggression'. *Journal of Community Psychology,* 37(6): 737 - 753.

Newcomb, T. (1961) *The acquaintance process*. New York: Holt, Rinehart & Winston.

Prell, C. (2012) *Social Network Analysis* London, Sage Publications Ltd.

Takács, K. (2001) 'Structural Embeddedness and Intergroup Conflict'. *Journal of Conflict Resolution,* 45(6): 743 - 769.

Tolsma, J., I. van Deurzen, T.H. Stark and R. Veenstra (2013) 'Who is bullying whom in ethnically diverse primary school? Exploring links between bullying, ethnicity, and ethnic diversity in Dutch primary schools'. *Social Networks,* 35(1): 51 - 61.

Zemljič B. and V. Hlebec (2005) 'Reliability of measures of centrality and prominence'. *Social Networks,* 27(1): 73 - 88.