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Sentiment Polarization and Balance among Users in Online Social Networks

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ABSTRACT

Communication within online social network applications enables users to express and share sentiments electronically. Existing studies examined the existence or distribution of sentiments in online communication at a general level or in small-observed groups. Our paper extends this research by analyzing sentiment exchange within social networks from an ego-network perspective. We draw from research on social influence and social attachment to develop theories of node polarization, balance effects and sentiment mirroring within communication dyads. Our empirical analysis covers a multitude of social networks in which the sentiment valence of all messages was determined. Subsequently we studied ego-networks of focal actors (ego) and their immediate contacts. Results support our theories and indicate that actors develop polarized sentiments towards individual peers but keep sentiment in balance on the ego-network level. Further, pairs of nodes tend to establish similar attitudes towards each other leading to stable and polarized positive or negative relationships.

Keywords

Social Network Analysis, Ego-Network Analysis, Node Polarization, Sentiment Dissemination

INTRODUCTION

The spread and popularity of social network applications in the Internet allow for a comprehensive and large-scale analysis of user behavior in online environments. There has been a variety of seminal research regarding the existence of sentiments or emotions in such communication channels dating back more than 20 years. Rice and Love (1987) conducted a study concluding that computer-mediated communication does in fact allow for the exchange of emotions despite the inherent absence of non verbal communication parts. Subsequent research confirmed the existence of emotions and sentiments in various computer-mediated communication channels such as discussion boards, micro-blogging services and other social network applications (Belkin, Kurtzberg and Naquin, 2006; Bollen, Pepe and Mao, 2009; Derks, Fischer and Bos, 2007; Doods and Danforth, 2009; Thelwall and Wilkinson, 2009).

However, we currently lack understanding of exact interaction traces of micro-level interaction and the role of sentiment for triggering processes or even cascades of affective influence among users in online social networks. To address this gap, we propose to adopt a social network perspective that models users as nodes and aggregates exchanged messages as links within complex social networks. Such a perspective enables explicating the micro-level processes of social influence that happen in actor communities and that might at least partially explain why actors (re-) act in a certain way. In particular we are concerned with affective influences brought about by the sentiment valence of messages to which an online actor is exposed. Such influences can bring about dissemination processes that could explain emerging effects like a main tonality of some online community or a separation of a group. To study this aspect of message exchange in communities, we performed a classification of sentiments embedded in textual communication and mapped their distribution onto network links. With this process we can study the valence of unfolding relationships and actors in online social networks and the influence and exchange of sentiments. The focus of the analysis lies on network nodes and their embeddedness within their ego-network. An ego-network represents a subset of the complete network topology with a focal node in the center, the ego node, and all direct communication partners. The transmitted messages are analyzed regarding sentiment distribution at a local level of the relationship between communication pairs and at a global level within ego-networks. In particular we theorize that there are important effects of node polarization, balance and sentiment mirroring within online communication dyads that might explain online sentiment distribution and diffusion. The research question for this paper can be formulated as: "What typical distributions of polarized and balanced relationships expressed with exchanged sentiments can be identified and what insights regarding human behaviour in online environments can be derived?" Answers to this question can be used to gain insights about applicability of social science theories and support the understanding of communication mechanisms in online environments.

RELATED WORK

In addition to research about the impact and spread of emotions and sentiments in online networks, there has been research covering real life interactions. In 2009, Fowler et al. have identified happiness spreading effects among humans and the emergence of clusters of happy and unhappy people over time. (Fowler and Christakis, 2009)

Thelwall and Wilkinson analyzed the existence of sentiments and emotions in online social networks. Findings suggest that positive emotion is present in about two thirds of the analyzed comments. Negative emotion is much less present than positive emotion and is furthermore not associated with gender. It has been shown that Social Networking Sites represent an emotion rich environment. (Thelwall and Wilkinson, 2009)

Based on the occurrence of sentiments in online networks, further research effort aimed at analyzing the consequences of affect in social networks. Bollen et al. have addressed a research question dealing with collective emotional states and various socio-economic phenomena. Results imply that collective emotional states can be found in social networks and certain real world events have a measureable influence within social networks. (Bollen, Goncalves, Ruan and Mao, 2011; Bollen et al., 2009)

Research about the influence of emotions in online environments was done by Schweitzer and Garcia (2010) who have developed an agent-based framework to model the emergence of collective emotions helping to understand and predict the emergence of collective emotions based on the interaction of agents with individual emotional states.

Further research has shown the existence of emotion-driven user communities and collective emotional states and their influence on community life. Results corroborate the influence of sentiments on other nodes and the existence of emotional clusters with identical sentiment polarization (Chmiel, Sienkiewicz, Thelwall, Paltoglou, Buckley, Kappas and Holyst, 2011; Mitrović, Paltoglou and Tadic, 2010).

THEORETICAL FRAMEWORK

For our analysis on the role of sentiment for affective social influence effects in online social networks, we can draw from a variety of academic contributions that theorized positive or negative network relationships among people (Belkin et al., 2006; Brzozowski, Hogg and Szabo, 2008; Huang, 2009; Kunegis, Lommatzsch and Bauckhage, 2009). Other research focused on the implications of affective polarized relationships on interpersonal relationships and emphasizes the prevalence of positive or negative relationships in social networks (Labianca and Brass, 2006). Polarized relationships represent a certain actor's attitude towards a communication partner. Hence, the sentiments embedded within messages transmitted among users should exhibit a bias towards either positive or negative polarization. Based on this assumption and in addition to the one-sided view of actor's attitude, this study is focussed on bi-directional network relationships by including reciprocal communication behaviour and analyzing the distribution of reciprocal exchanged sentiments in communication dyads.

Interpersonal behavior theory deals with human behaviors that complement each other. The interpersonal circle by Kiesler outlines witch behavioral patterns relate to each other. In the frame of his *Interpersonal Complementarity*, each action triggers a response and each response adapts to the previous action so that these will be repeated with high probability, e.g. friendliness invites friendliness (Kiesler, 1983).

Emotional contagion describes the issue that human emotional states are influenced by other people through interaction and communication. People consciously and unconsciously adopt emotional states of their communication partners. Although emotional contagion theory is essentially based on the effect of interpretation of non-verbal parts of human communication which are suppressed in online communication, it has been shown that emotional contagion is also present in online environments (Belkin et al., 2006; Hatfield, Cacioppo and Rapson, 1993).

Miller et al. have analyzed sentiment dissemination through hyperlink networks and report that nodes are strongly influenced by their communication partners (Miller, Sathi, Wiesenthal, Leskovec and Poots, 2011). In addition, they found that sentiment polarization is more likely to be present as the length of communication chains increases. Based on these findings regarding the influence of sentiments and the adoption of reciprocal attitudes, we state:

H1) Communication partners mirror exchanged sentiments leading to reciprocal equally polarized relationships.

Within the second part of the study, we extend the analysis by looking at a node's complete set of communication partners. Our main emphasis lies on the relationship between the polarizations of individual communication links in respect to the expressed attitudes towards all communication partners especially on possible balance effects within a holistic analysis of the communication behaviour.

To explain possible differences regarding the polarizations of affective ties, we can further apply attachment theory. This approach addresses the different levels of perceived importance of individual relationships between a focal actor and her contacts, e.g. the relationship between mother and their children (Cassidy and Shaver, 2008). In our context, attachment theory suggests that polarization of relationships should be conceptualized as a property of the links or relationships rather than being a characteristic of the people themselves. This leads to the expectation that nodes within networks should, despite their polarized attitude towards specific communication partners, express a rather balanced pattern when looking at the whole set of all their links to contacts.

This notion of sentiment as a relational rather than a nodal attribute is in accordance with Heider's (1946) theory of social balance. It focuses on the distribution and arrangement of positive and negative relationships in social networks. Balance theory describes certain small structural patterns and common principals that lead to stabile network structures on the basis of 'the friend of my friend is my friend' and 'the enemy of my friend is my enemy'. Heider's social balance theory describes the interplay of positive and negative relationships in network patterns among triples of nodes and therefore supports expectations regarding possible balance effects within all communication links of a specific node. Leskovec et al. have analyzed the distribution of positive and negative links within social networks. They found evidence that certain pattern configurations in accordance with social balance theory are present at a local network level and proved the applicability of Heider's theories in online environments (Leskovec, Huttenlocher and Kleinberg, 2010). Based on attachment theory and social balance theory regarding local configurations of positive and negative ties, we expect a sentiment balancing effect when looking at ego's complete group of contacts. In other words, the polarized relationships of a focal actor are balancing out in ego-network (rather than being only negative or positive):

H2) Within the whole group of contacts, nodes tend to develop a balanced state regarding transmitted sentiments across all their communication links.

Social networks are known to belong to the class of scale-free networks showing scale free degree distributions which are dominated by few highly connected nodes and a majority of nodes with a small node degree (Barabasi and Albert, 2002; Barabasi and Bonabeau, 2003; Caldarelli, 2007; Panzarasa, Opsahl and Carley, 2009). Hence, the communication activity of nodes within social network is unequally distributed - few nodes are responsible for the majority of network edges.

Results of an own exploratory study (manual reconstruction of 10 online discussion threads) have shown, that in online discussions, topics are being discussed and people are sharing their opinions and express agreement or disagreement. Over time, implicit groups of people with same opinions are emerging, supporting each other and prolonging the discussion with people having different opinions. This mechanism was found early-on in different online discussion boards independent of the discussion lifetime and the corresponding network size. Nodes with "relative" high communication activity are likely involved in different communication threads dealing with both agreement and disagreement and serving as some kind of moderator. Based on the presence of typical mixed interaction patterns indicating that nodes have the tendency to develop towards a balanced state within their personal communication network and including the communication mechanism described above, we expect a correlation of node degree and the expression of well-balanced states.

H3) Online social networks exhibit a correlation between node degree and the expression of a well balanced state across all communication links independent of network size.

DATA FOR ANALYSIS

The data basis for the analysis covers online interaction data from various social network types including information from discussion forums, internet relay chats, micro-blogging services and newsgroups in the internet. The networks differ in terms of size, duration and communication intensity. Due to the abstract level of our propositions and the intention to derive insights about general communication mechanism, this data heterogeneity is appropriate.

The forum discussions were retrieved from the *BBC* website as well as the online portal *Digg.com.* The first dataset covers all discussions from seven *BBC* message boards and covers a time span from 2005 till 2009. The *Digg.com* forum data is a complete crawl of all story related discussions and covers the months February, March and April of the year 2009. The IRC dataset includes chat interaction from the *Ubuntu* e-community and contains chat dialog recordings from 57 different communication channels and covers a period between summer 2005 and 2010. The micro-blogging dataset is based on *Twitter* posts from February 2010. The newsgroups dataset includes a corpus of Usenet newsgroups with the complete posting history for several Austrian newsgroups from 1995 to summer 2010.

Each data source has a specific underlying data structure, determined by certain technical properties of the internet service in use. To overcome the disadvantages of heterogeneous source data structures, all data was transferred into a coherent event-based data model based on the approach of Trier (2008). The data model used for event-driven network analysis differs from other network data models and has a strong focus on network dynamics (Trier, 2008). The data model consists of three main elements: networks, nodes and communication events, so called linkevents. The linkevents can be generally described as human interaction in social networks and are based on exchanged textual messages among users that are aggregated to network links among nodes (see Figure 1). Due to different quantities of the source data, the number of network entries per data set differs (see Table 1).

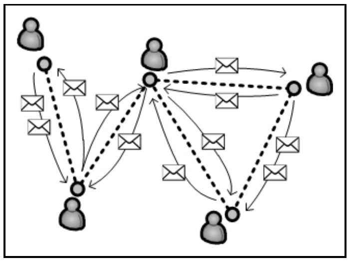

Figure 1: Network links as aggregations of messages

Dataset	Number of networks
Forum Dataset I	1657
Forum Dataset II	8576
Chat Dataset III	1925
Micro-blogging Dataset IV	628
Newsgroup Dataset V	1001

Table 1: Number of networks in database

ANALYSIS METHODOLOGY

The event-based data model allows for the detailed reconstruction of online social networks. The methodology described below is tailored to this data model utilizing the aggregation of single messages to network links to enable a fine grained analysis of the relationship of sentiments embedded in textual messages and communication links.

As a first step, the exchanged messages in all networks have been analyzed regarding their embedded sentiments. That was done with special developed classifiers that represent the state-of-the-art in sentiment classification and were developed as part of the European FP7 project "Collective Emotions in Cyberspace" (Paltoglou, Gobron, Skowron, Thelwall and Thalmann, 2010; Thelwall, Buckley and Paltoglou, 2011; Thelwall, Buckley, Paltoglou and Cai, 2010). The classification consists of two phases. In the training phase, the classifiers are using a set of human annotated documents from which the algorithms learn the characteristics of the sentiments. In the second phase, the software classified the content of each linkevent regarding the sentiments of the text. Each analyzed message is rated regarding included positive and negative sentiments with a scale ranging from 1-5 for positive and (-1) - (-5) for negative sentiments. To overcome limitations regarding the accuracy of the classification results (Thelwall, Buckley and Paltoglou, 2011), the sentiment spectrum of the classifier was converted into four disjoint categories according to a specified scheme (see Figure 2).

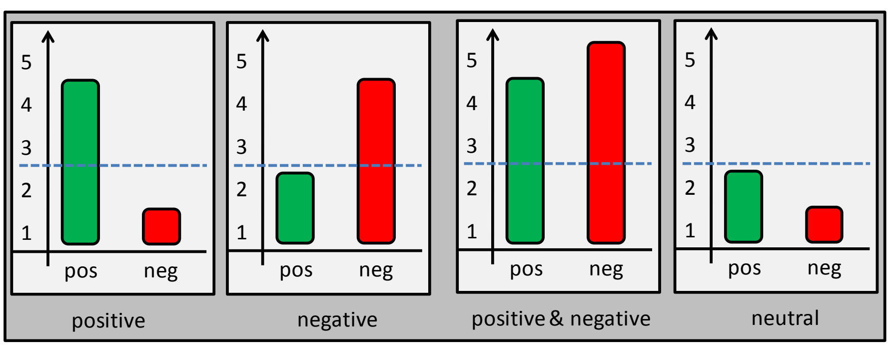

Figure 2: Sentiment categorization schema

The basic schema differs between four disjoint categories of sentiment classification (positive, negative, both positive and negative and neutral). Due to the computational reason that each message contains at least a sentiment value of one, a threshold level of three is defined. A classification with a positive result above and a negative result below the threshold is categorized as positive and vice versa. If both the positive and the negative results are above the threshold level, the message is categorized as both positive and negative. If both results are below the threshold level, the linkevent is classified as neutral expressing the fact, that the text contains neither positive nor negative sentiments at a meaningful level. Within this analysis, only positive, negative and neutral messages are incorporated to derive results regarding polarization and balance effects.

This analysis is focused on influence and dissemination of sentiments and resulting polarized links within ego-networks, which represent a subset of the network topology and is defined as a node in the centre, the ego node, and all of its communication partners while the rest of the network is suppressed (see Figure 3).

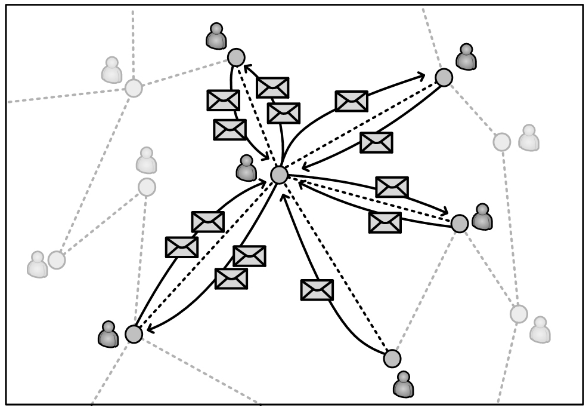

Figure 3: Ego-network extraction

Each of the aforementioned hypotheses 1-3 is addressed with an analysis part. To derive meaningful statements about link and ego-network polarization, certain minimum requirements for links among nodes and ego-networks are defined which determine the interpretability of the data. Ego-nodes have to transmit a minimum of four messages towards a specific node to create an adequate link to enable the emergence of polarization effects. Nodes must have more than three different communication partners to represent a meaningful ego-network. Both requirements are necessary to exclude trivial cases of polarization effects.

As a preliminary step, each of the outgoing network links within ego-networks is analyzed regarding a possible link polarization. The following formula (1) is used to determine the polarization of nodes towards communication partners on link i. Hence, only messages transmitted from the ego-node across link i are taken into account.

$$\boldsymbol{pol_i} = \frac{\#\mathbf{messages_{positive}} - \#\mathbf{messages_{negative}}}{\#\mathbf{messages_{total}}} \tag{1}$$

The number of positive and negative messages is subtracted and the result is divided by the total number of messages. The messages with both positive and negative sentiments (see Figure 2) are ignored due to their not assignable nature.

The analysis regarding H1 is focussed on polarization effects of reciprocal connections. The polarization of the ego-node n towards the communication partner m is determined together with the opposite attitude of node m towards node n with formula (1). The absolute difference of both polarization values is computed and the distribution is determined for intervals between exact mach (0) and maximal opposite polarization (2).

Regarding H2 and H3, analyzing balance effects within ego-networks and correlation between node degree and ego-network polarization, the same formula (1) is used. However, all messages transmitted from the ego-node to all communication partners are simultaneously incorporated in the analysis.

For the analysis of H3, the out-degree of all nodes is computed using an adjacency matrix. Due to the heterogeneous quantitative characteristics of social networks, the degree threshold is calculated for each network separately. The 50% best connected nodes within networks are interpreted as having a “high” node degree; all other nodes are interpreted as having a “low” node degree. For each node, the two features node degree and ego-network polarization are determined and stored in a 2-dim matrix to perform a chi-square test.

The aforementioned calculations are repeated for the five datasets including all networks and nodes together with their ego-networks under consideration of the quantitative requirements mentioned above.

RESULTS

We have analyzed the descriptive sentiment distribution within the datasets (see Figure 4). The datasets differ in terms of their sentiment distribution. The positive fraction ranges from 2% to 49%. The highest share is within the micro-blogging dataset. The negative sentiment linkevents have a share from 7% to 50% with a peak at the newsgroup dataset. The fraction of both positive and negative linkevents ranges from 7% in the newsgroup dataset to 36% in the forum dataset 1. The percentage of neutral messages has the lowest value in forum dataset 1 and the highest proportion in the newsgroup dataset.

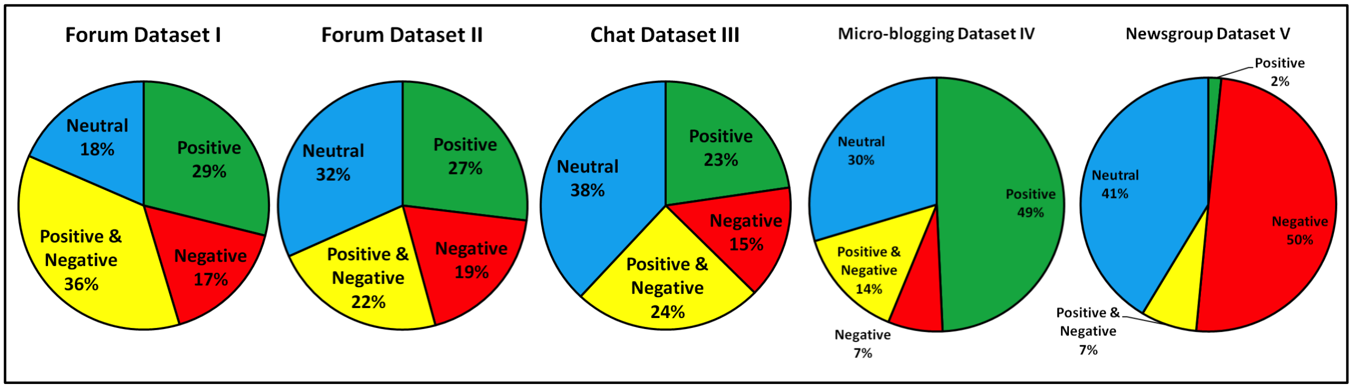

Figure 4: Sentiment distribution

Figure 5 includes the results of the analysis regarding the share of polarized links within the networks. The distributions differ among the five datasets. The highest share of can be found within the micro-blogging dataset, the lowest part is present in the chat dataset. The distribution of polarized links is separated according to 0.1 range intervals from strong negative polarization (-1) to strong positive polarization (+1) as a result of formula (1). Except the chat dataset, a tendency towards polarization having peaks at the positive and negative extremes can be seen exhibiting a **U** or **W** shape.

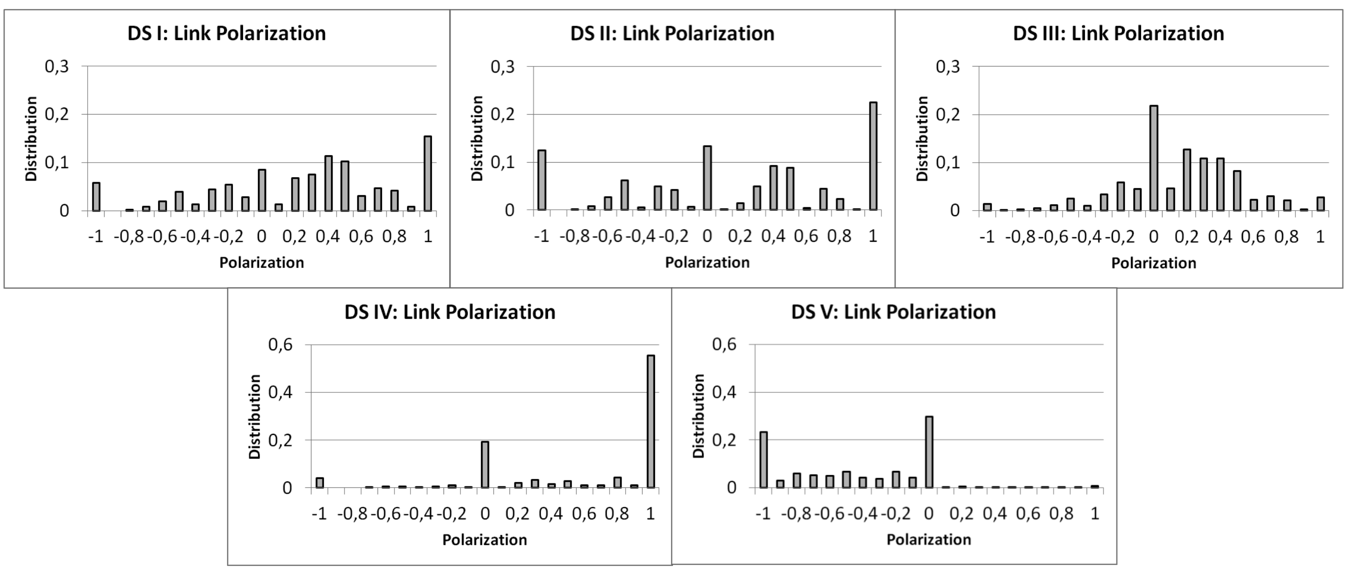

Figure 5: Link-polarization distribution

Figure 6 includes the results of analysis part one focused on sentiment mirroring effects on reciprocal links. The polarization value is calculated for both directions separately. The distance between both values is calculated and presented together with the number of samples, the average distance, standard derivation and the correlation coefficient (DS IV could not be used due to insufficient number of valid results).

Results exhibit correlations regarding the exchanged sentiments on reciprocal network links. The average distance ranges from 0.34 to 0.62. The majority of network relationships only exhibit a small distance between both polarization values. Between 57% and 78% of all analyzed links express reciprocal similar sentiments with results ≤ 0.6. H3 predicting equally polarized network links can therefore be supported.

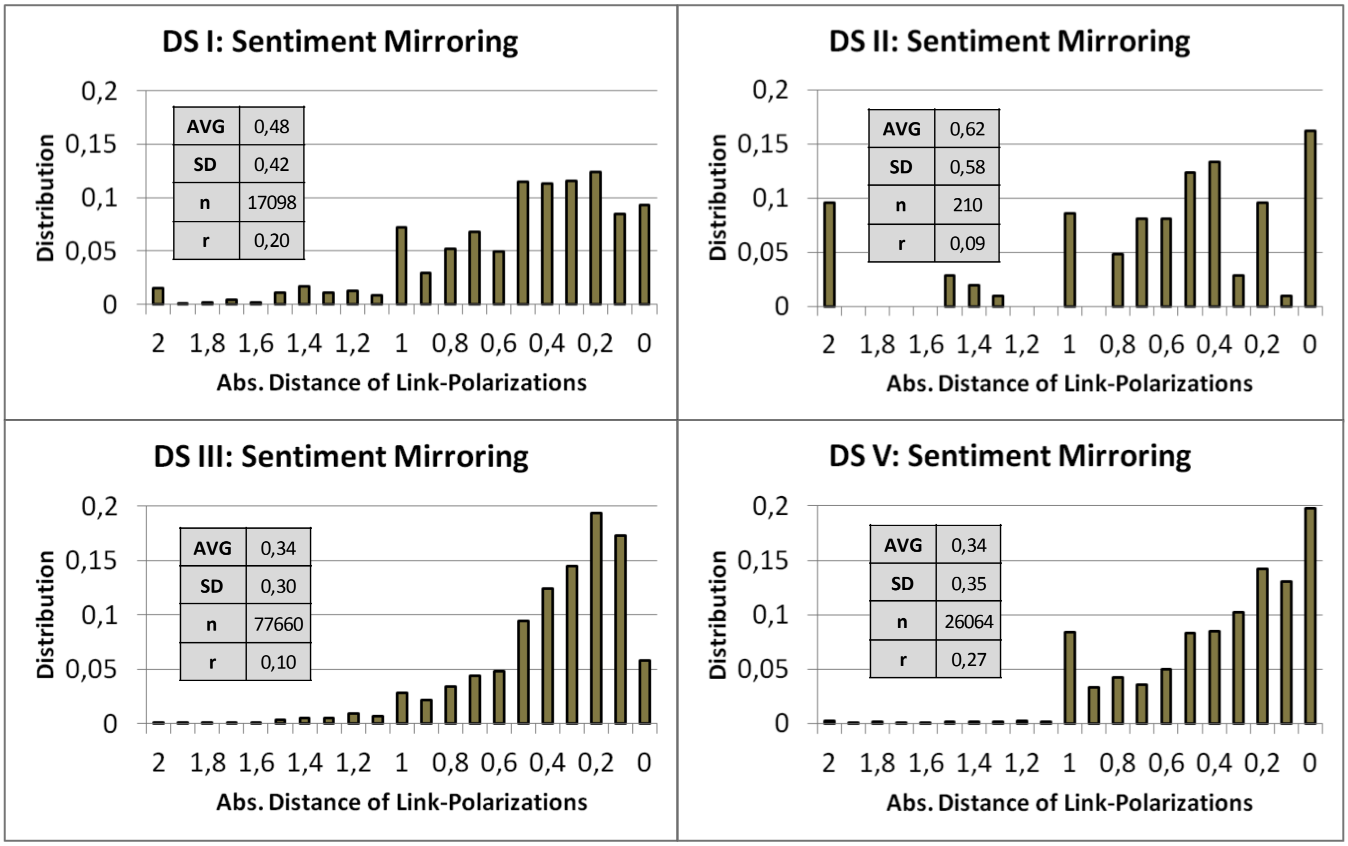

Figure 6: Sentiment mirroring distributions

Figure 7 shows the polarization results for both ego-networks (black bars) and individual links (gray bars). The bars represent the percentage share of polarizations according to formula (1) separated by 0.1 intervals from (-1) to (+1).

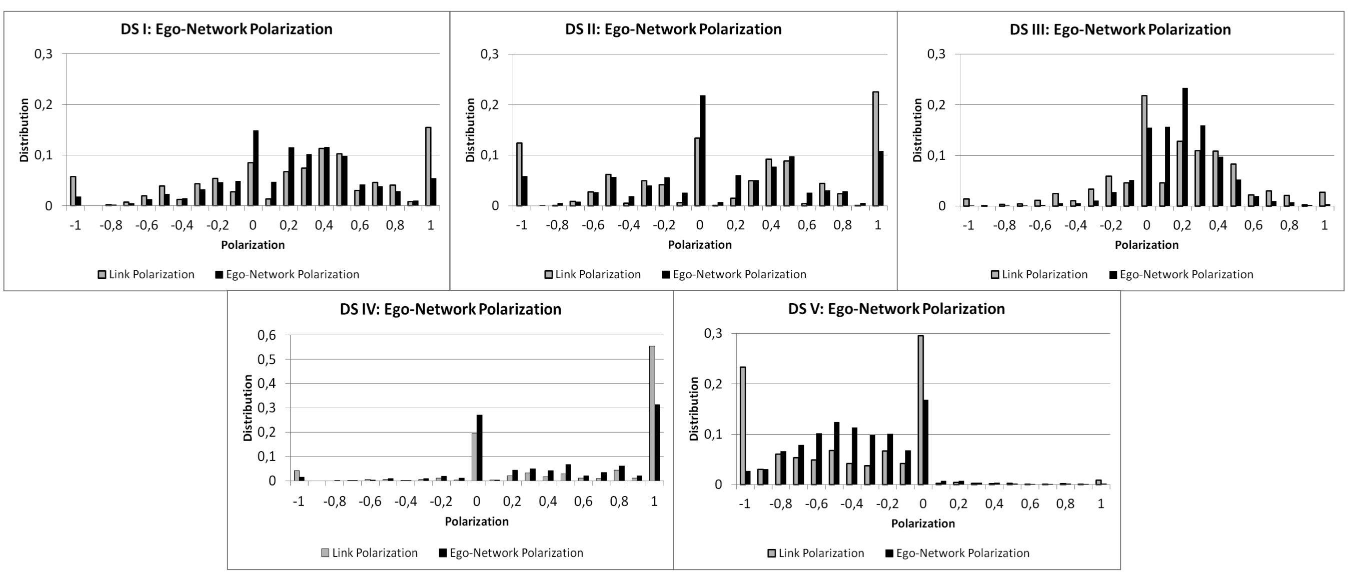

Figure 7: Ego-network polarization distribution

Compared with the link polarization (gray), a tendency towards balanced ego-node states can be seen. Except the dataset IV, the graphs do not exhibit a **U** or **W** shape but instead having a peak in the middle expressing a slightly positive tendency. In case of the newsgroup dataset, the peak is slightly negative between I = [-0.6,-0.4] which is in accordance with the sentiment distribution of the population with a strong share of negative sentiment. In comparison with the link polarization results, ego-networks exhibit a tendency towards a well balanced state regarding expressed sentiments supporting H2.

Figure 8 conveys the results of the analysis regarding H3. The analyzed ego-networks have been categorized according to their outgoing node degree and their ego-network polarization. The absolute polarization values are sorted according to three intervals from low to high. Results are stored in a crossable.

DS I

		Polarization			
		low (p < 0.33)	med (0.33 <= p < 0.66)	high (0.66 <= p)	Σ
Degree	low	1910	1515	1053	4478
	high	4446	2343	620	7409
	Σ	6356	3858	1673	11887

p < 0.01

DS II

		Polarization			
		low (p < 0.33)	med (0.33 <= p < 0.66)	high (0.66 <= p)	Σ
Degree	low	2075	1856	2071	6002
	high	7319	5121	2932	15372
	Σ	9394	6977	5003	21374

p < 0.01

DS III

		Polarization			
		low (p < 0.33)	med (0.33 <= p < 0.66)	high (0.66 <= p)	Σ
Degree	low	6249	2338	400	8987
	high	9907	986	47	10940
	Σ	16156	3324	447	19927

p < 0.01

DS IV

		Polarization			
		low (p < 0.33)	med (0.33 <= p < 0.66)	high (0.66 <= p)	Σ
Degree	low	45	20	60	125
	high	227	68	223	518
	Σ	272	88	283	643

p = 0.27

DS V

		Polarization			
		low (p < 0.33)	med (0.33 <= p < 0.66)	high (0.66 <= p)	Σ
Degree	low	1901	1550	1382	4833
	high	2036	2622	1262	5920
	Σ	3937	4172	2644	10753

p < 0.01

Figure 8: Correlation between node degree and polarization

Results exhibit a significant correlation between node degree and ego-network polarization supporting H3. Except dataset IV, the independence of both features needs to be rejected. The distributions exhibit a correlation showing low polarization in combination with high-node degree. Due to a large scattering of network sizes used for this analysis, the effect is independent of specific network size or node degree levels.

INTERPRETATION

Our data suggests the existence of polarized network links (positive or negative). However, some network links also express a balanced state, either with the exchange of an equal amount of positive and negative or with neutral messages. One can conclude that people participating in online networks either do take a certain positive or negative attitude towards people or maintain a rather balanced position towards their communication partners. Our theories predicting polarized relationships among users of social interaction can be supported by analyzing sentiments embedded within exchanged messages. However, subject to the specific context, neutral or balanced relationships are also present in social networks.

Our research extended the one-sided view of nodes in ego-networks and their outgoing communication by analyzing bi-directional relationships. Results show that communication partners are likely to respond in a similar way expressing the same attitude towards the ego-node. Social networks exhibit a trend to establish links with a corresponding view or attitude between both nodes leading to reciprocal identical polarized relationships.

In contrast to the presence of polarized network links, sentiments in ego-networks developed towards a balanced distribution. A polarized attitude of users towards other nodes can therefore be seen as a property of the relationships themselves rather than as a node attribute. The existence of polarized users in general cannot be supported. Instead, the users express a balanced state at a global level together with specific positive and negative relationships at the local level within dyads. Within the third part of the analysis, a significant correlation between node degree and the expression of a well-balanced state can be found indicating a certain moderating role of central actors independent of network size or communication activity.

CONCLUSIONS

This empirical study is focused on identifying and explaining patterns of polarization effects in online social networks. The comprehensive data basis allows for the discovery of general regularities independent of specific communication types or application contexts. Our results support the role of previous social science theories in online network environments and serve as a basis for future research.

Our data supported the existence of polarized network links as well as balance tendencies within ego-networks. In accordance with a variety of social science studies, relationships with an expression of positive or negative attitudes can be found by applying a sentiment analysis of message exchange. This polarization can be seen as an attribute of the network links rather than being an actor property due to balanced sentiment distributions within ego-networks. A significant correlation between node degree and the expression of a well-balanced state is found emphasizing a moderating role of central actors.

Despite this local polarization compared to global balance and in accordance with Kiesler's *Interpersonal Complementarity Theory* and *Emotional Contagion* theory, users are likely to mirror exchanged sentiments in reciprocal message exchange leading to stable and polarized relationships.

This study analyzed sentiments in messages without information about the actual content of the communication. Further research could extend the analysis by integrating a content perspective and combining sentiment with content or topic dissemination. The analysis scope could be further extended from links to network motifs and the influence of social network effects such as reciprocity or transitivity in social networks.

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