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Personalized Social Connectivity and Reputation

Monitoring Dynamics in Online Networks with Aigents Platform

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***Abstract*—The paper describes the approach and solution for personalized assessment of social interaction patterns in online social networks. The approach and the solution are used for temporal monitoring and study of social communication dynamics, as well as for the personal reputation management.**

***Keywords*—Big data; communication pattern; personalization; social network**

I. Purpose

Originally, this work has started with the intention to design and develop artificial psyche for robot operating with objects in the Internet, such as web pages and news feeds [1]. The intention was to make this robot capable of self-awareness in human environment, with motivations similar to those in other works in domain of robotics, such as [2] and [3]. However, while modeling aspects of consciousness in social environments, an idea of capturing true contexts of social interactions between real people, extracting it from social networks, arose [4]. During that study, the importance of this area's development is that it provides more problems to solve and promises much more practical application than the original goal of robot construction became really apparent. Quantitative account for social interactions being translated into measurable reputation and even convertible into financial values had been imagined in literature [5]. Furthermore, different applications based on such account became widely popular as Web reputation systems [6]. Finally, so-called "Social Credit" system, already being implemented at scale of ¼ of the population in China, with all social interactions captured and translated into value, radically affecting life of every citizen [7]. Thus, we have proposed the instrument to give user a tool to study temporal social dynamics of their own, in context of interactions with other members of the social environment so that the person could benefit of it.

II. Background/Significance

Initial design of system capable for comprehension of social context was based on earlier works on multi-agent representation of consciousness and intelligence defined as "ability to reach complex goals and complex environments using limited resources" [8]. Further, it have been extended to account for social context, with notion of "social evidence-based resource-constrained knowledge representation" as described in latest publications [9], [10] where more field experiments and literature study have been conducted to confirm the validity of the model and the design.

The confirmation of the model came out from earlier comprehensive phenomenological study [11] where every possible outcome of computable model has been backed up with recorded evidence in domain of social psychology. Moreover, in respect to specifics of interactions in social networks, it has been found that possibility of impact of manipulations by means of online social media can be huge [12]. Finally, the effect of such impact can be affecting not just behavioral patterns of a human or society, but their physical health also [13], which makes importance of work in this direction hardly overestimated.

III. Method

To implement the assessment and temporal monitoring of personal social dynamics in terms of reputation and social connectivity patters, we have used design developed earlier [14]. The design is briefly outlined in Fig. 1. In this design, using different social networks the person of study is connected to, online interactions are extracted, recorded and processed as it will be discussed further.

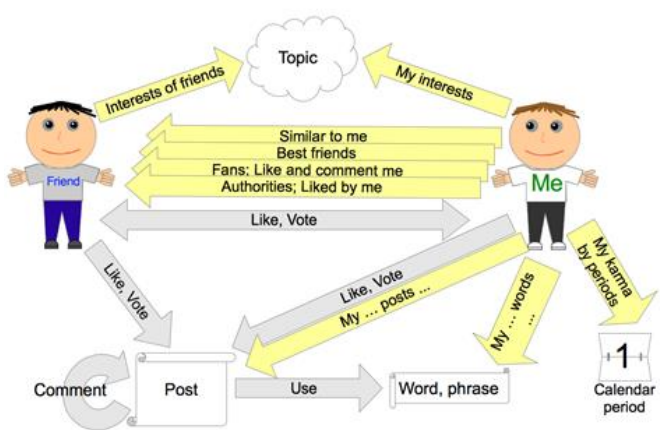

Fig. 1. Design of the system capable of extracting context and dynamics of online inter-personal interactions in social networks expressed in terms of posts, comments, "likes" (as in Facebook, Google+ and VKontakte) and "votes" (as in Steemit and Golos).

For the purpose of the study, five social networks were used. Three of them were private social networks with limited access to information via public "application programming interface" (API) – these networks were Facebook, Google+ and VKontakte. Two other social networks were community-owned ones based on block-chain technology with unlimited access to information via API - Steemit and Golos. The data

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extracted from social networks were user's posts, comments of other users to the posts and reactions directed toward these posts and comment. For reactions we used "likes" (called so in Facebook, Google+ and VKontakte) and "votes" (in Steemit and Golos), meaning that the acting person shared an opinion expressed in the post or comment. The texts extracted from original posts and comments were converted into feature vectors associated with the posts and comments [14]. The feature vectors were cleaned of frequently used words, such as articles and interjections, and were normalized on basis of relative popularity of the words, according to dictionaries and frequencies of usage for the given language, namely English or Russian. Furthermore, feature vectors associated with posts and comments were converted into feature vectors identifying particular users.

Given the feature vectors representing posts, comments and users, "natural classifications" for each user were derived to figure out domains of users' interests according to the approach described in [15]. From the authored comments and "likes" or "votes" on these posts and comments, the quantitative parameters were evaluated according to notions and definitions in earlier research [16] as discussed below. Finally, in the scope of this work, evaluation of these parameters has been bound to temporal axis within time intervals of different durations and correspondence of them to real-life observations has been studied qualitatively.

On the basis of feature vectors representing topics of interests, users, posts and comments, along with "likes" and "votes" given to them, multiple relationships were inferred. These relationships could indicate different sorts of connections between the primary user and their friends and posts and comments of both, assuming L_{ij} can be used to denote the number of "likes" or "votes" other user j gives to the posts and comments made by the given user i. Further, in the formulae C_{ij} is denoting the number of comments the user j makes in regard to posts/comments made by the user i.

My interests – Listed clusters of words identifying topics of groups of posts and comments associated with use of these words, either written by the user of study or presented in comments that the user was identifying as "liked" or "voted" for. It was inferred with adaptive K-means clustering (with no K number of clusters given in advance) where the lists of clusters and the lists of features identifying them were built incrementally and simultaneously to reach the optimal K number.

Interests of my friends – Listed clusters of words identifying topics of groups of posts and comments, similar to the above, while not representing the user of the study themselves, but rather their connections in social network.

Similar to me – Ranked other users according to *similarity* metric between each user and their connections calculated using feature vectors extracted from users' posts and comments with normalized overlap between the two vectors evaluated as mutual similarity measure between the users.

Best friends (and colleagues) – Ranked other users based on *friendship* metric treated as symmetric strength of positive relationship based on value of mutual "likes" or "votes" between two users $L_{ij}*(L_{ji}+C_{ji})$, normalized by the maximum number for given friend j of user i across all J users as follows.

$$B_{ij} = L_{ij}*(L_{ji}+C_{ji}) / Max_{j=1,J} (L_{ij}*(L_{ji}+C_{ji}))$$

Fans (and followers) – Ranked users by *adherence* metric as strength of asymmetric, or directed positive relationship, which could be evaluated through the amount of "likes" or "votes" and comments that the other user gave to the posts of the primary user. The metric was denominated by returned "likes"/"votes" and comments, so that a complete fan was one who paid more attention to primary user while the latter paid the least amount of attention to the fan.

$$F_{ij} = ((L_{ji}+C_{ji})/(1+L_{ij}+C_{ij}))/Max_{j=1,J} ((L_{ji}+C_{ji})/(1+L_{ij}+C_{ij}))$$

Like and comment me – Simplified version of "fans" without denomination by mutuality of positive relationship.

$$F'_{ij} = (L_{ji}+C_{ji}) / \mathrm{Max}_{j=1,J} (L_{ji}+C_{ji})$$

Authorities (and leaders) – Listed users according to *authority* metric, also known as "thought leader" or "opinion leader" or "the one that I listen to", which can be described as metric opposed to *adherence*, as asymmetric positive relationship. It corresponded to the amount of attention, i.e. the number of "likes" or "votes", paid by primary user to third ones, denominated by the amount of attention ("likes"/"votes" and comments) returned by them.

$$A_j = ((L_{ij}+C_{ij})/(1+L_{ji}+C_{ji})) / Max_{j=1,J} ((L_{ij}+C_{ij})/(1+L_{ji}+C_{ji}))$$

Liked by me – simplified version of "authority" without denomination by mutuality of positive relationship.

$$A'_j = (L_{ij}+C_{ij}) / Max_{j=1,J} (L_{ij}+C_{ij})$$

My karma by periods – Periods ranked by *karma* metric as evaluation of sum of "likes" and "votes" granted to the user within the given period t across a set of periods T, normalized to the best achievement across all periods. The notion of "karma" was used here as incremental value of reputation, earned by the user in the given time interval spanning over all periods involved in the analysis.

$$K_{it} = \sum_{j,t} (L_{ij}+C_{ij}) / Max_{t=1,T} \sum_{j,t} (L_{ij}+C_{ij})$$

My favorite words – Listed words from user-specific feature vector, limited to simple "single word" kind of feature, across all posts and comments of the primary user, ranked by relative frequency of use.

My words by periods – Did the same with features grouped by periods of time according to dates of posts and comments. This kind of profiling has turned to be useful when aligned with *karma* metric discussed above, so the two can be correlated as it will be discussed in the results later.

Words liked by me – A list of "words" ranked according to the amount of "likes" or "votes" and comments given by the primary user to the posts and comments containing them.

My best words – A list of "words" used by the subject of the study in his or her own posts ranked according to the amount of "likes" or "votes" and comments that these posts received on behalf of other users.

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My posts liked and commented – Posts by the primary user ranked according to the amount of "likes" or "votes" and comments received from other users.

The definitions made above may raise questions regarding the justification of the terms "karma" and "reputation" and the respective formula in particular. The terms themselves are widely used in different applications while applicability of them is discussed in literature [5], [6] and our use of them seems quite compatible with that discussion. The impact of "likes"/"votes" of comments raise more questions. On the one hand, the act of giving "like"/"vote" to a post is an explicit conscious act that should be given more importance than attention paid implicitly by fact of commenting the post. On the other hand, the act of "liking/voting" is very simple and not resource consuming, compared to the amount of efforts the author of comment is investing into the act of commenting, so the latter should be valued as more important, from this perspective. At this point it was decided not to try to solve this problem and gave both kinds of attention equal rights.

IV. Results

For the purpose of the study, for the participating user, the parameters described above were evaluated with Aigents computational platform and presented in raw JSON data and formatted HTML reports. Raw JSON data were used to render graphs of social connectivity using Aigents web service and presented to users with few different options, as shown in Fig. 2.

The circle in the middle was representing the user himself/herself, while the circles around were indicating their social connections. On the very top, with saturated yellow color, there were those with greatest reputation and social capital from users' perspective; in other words these users were getting a lot of likes/votes and comments without being reciprocated. On the left and on the right, with medium yellow saturation there were people with similar level or social capital/reputation with user, — so that exchanges with them with likes/votes and comments were mutual. At the bottom, with low yellow saturation, there were people who provide the user with many likes/votes and comments, while the user did not pay them back often enough.

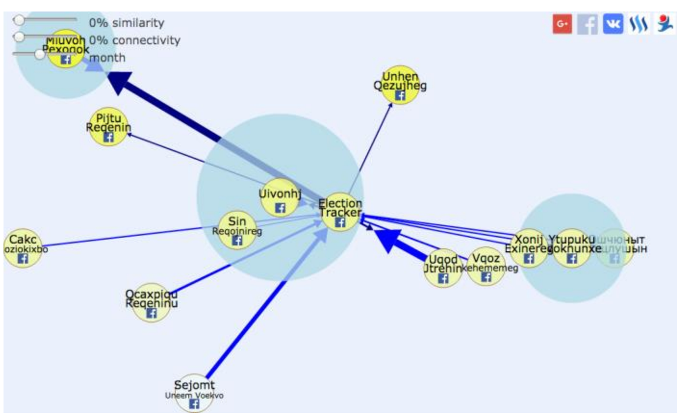
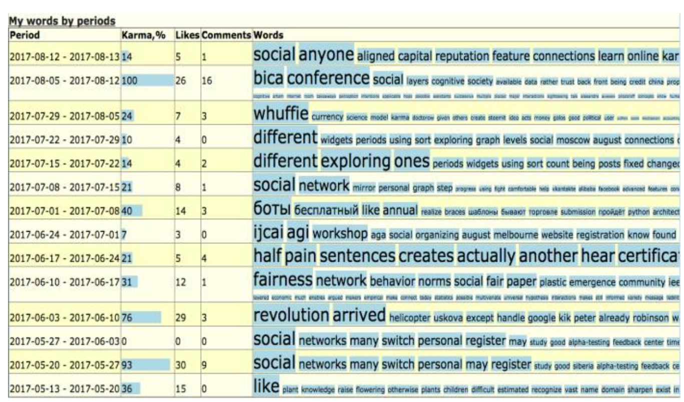


Fig. 2. Sample graph of social connectivity for each of social networks in the study with obfuscation of actual user names because of privacy concerns.

Topmost people on the graph could be thought as "authorities", or "those who I pay most attention to but they don't notice me". Below, there were "opinion leaders", or "those whom I pay more attention than they do to me". In the middle there were "friends" and "colleagues" who the user communicated with symmetrically. Below, there were "followers" or "those who pay more attention to me than I pay to them". Finally, at the very bottom, there were "fans", who paid a lot of attention to the user but the user barely returned it to them. That is, what we call reputation or "karma" in context of this work was rendered as vertical position of a person and saturation of yellow color. Calculation of this value might be imprecise because only communications in relation to the studied users' personal news feeds were accounted and didn't involve communications in other groups or other users' feeds.

Communication connectivity between the user of study and others around was represented with blue arrows. Relative lengths of the arrow between the user and his/her peers indicated the ratio of incoming and outgoing actions, namely, likes/votes and comments. Respectively, for the people above, links from the user directed to them were relatively longer. In turn, links to people below were relatively shorter. Moreover, widths of these arrows indicated relative intensity of communications with the given person compared to other partners on the graph. To indicate similarity between the user of study and other people in respect to the topics of interest the size of the light blue halo, around each circle, was used.

Since there could be many connections and partners on the same graph for given social network within the same time period, control widgets were available. First, the user could restrict rendered social connections by level of similarity with himself or herself. By default, no filter was set but the user could change it to see only those similar as 25%, 50% or 75% or more. Also, the user could restrict rendered social connections by the level of intensity of communications with them. By default, no filter was set, but the user could change it to see only the people with connectivity as 25%, 50% or 75% or more. Additionally, in order to study different temporal periods of their online activity, users could specify the period that they wanted their graph to be rendered for—1 day, 1 week, 1 month, 1 quarter, 1 year or all years spent online.



My words by periods

Period	Karma,%	Likes	Comments	Words
2017-08-12 - 2017-08-13	14	5	1	social anyone aligned capital reputation feature connections learn online kar
2017-08-05 - 2017-08-12	100	26	16	bica conference social layers cognitive society available data rather trust back front being credit china prop
2017-07-29 - 2017-08-05	24	7	3	whuffie currency science model karma doctorow given others create steemit idea acts money golos good political user
2017-07-22 - 2017-07-29	10	4	0	different widgets periods using sort exploring graph levels social moscow august connections
2017-07-15 - 2017-07-22	14	4	2	different exploring ones periods widgets using sort count being posts fixed changed
2017-07-08 - 2017-07-15	21	8	1	social network mirror personal graph step progress using fight comfortable help vkontakte alibaba facebook advanced features
2017-07-01 - 2017-07-08	40	14	3	боты бесплатный like annual realize braces шаблоны бывают горровне submission пройдёт python architect
2017-06-24 - 2017-07-01	7	3	0	ijcai agi workshop aga social organizing august melbourne website registration know found
2017-06-17 - 2017-06-24	21	5	4	half pain sentences creates actually another hear certifica
2017-06-10 - 2017-06-17	31	12	1	fairness network behavior norms social fair paper plastic emergence community iee
2017-06-03 - 2017-06-10	76	29	3	revolution arrived helicopter uskova except handle google kik peter already robinson w
2017-05-27 - 2017-06-03	0	0	0	social networks many switch personal register may study good alpha-testing feedback center time
2017-05-20 - 2017-05-27	93	30	9	social networks many switch personal may register study good siberia alpha-testing feedback ce
2017-05-13 - 2017-05-20	36	15	0	like plant knowledge raise flowering otherwise plants children difficult estimated recognize vast name domain sharpen exist in

Fig. 3. Temporal dynamics of relative reputation increment ("karma") aligned with values of relative attractiveness of the words in users' posts online.

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My friends by periods

Period	Karma,%	Likes	Comments	Friends
2017-08-12 - 2017-08-13	14	5	1	Ogvonic Mugqegjric Юшчюныт Цощлушын Sejomt Uneem Voekvo Unhen Qezujheg Cakc Noziokixbo Qoe Uqodunxok Änvojqogä
2017-08-05 - 2017-08-12	100	26	16	Uqod Jtrehin Miuvoh Pexoqok Qcaxpiqu Reqeninu Sejomt Uneem Voekvo [illegible]
2017-07-29 - 2017-08-05	24	7	3	Sejomt Uneem Voekvo Miuvoh Pexoqok Pijtu Reqenin Qcaxpiqu Reqeninu Vqoz Mkehememeg Ukhop Ukh Jujtu Jokvoog Pajhuwu Lupukaxxin
2017-07-22 - 2017-07-29	10	4	0	Puxitu Qiuluh Rtun Sejomt Uneem Voekvo Zekij Bcjrin Xonij Exinereg
2017-07-15 - 2017-07-22	14	4	2	Uivonhj Sejomt Uneem Voekvo
2017-07-08 - 2017-07-15	21	8	1	Uivonhj Eqov Onu Урьчя Муроныня Sejomt Uneem Voekvo Giyhek Jpikneg Okiy Qui Xay Ntaun Pajhuwu Lupukaxxin
2017-07-01 - 2017-07-08	40	14	3	Gquxipik Rikiqonre Vqoz Mkehememeg Piytuoq Tunnopunn Ytokncureg Pudip Xenoqq Uqpunbek Uxayuq Qcaxpiqu Reqeninu Unhen Qezujheg Qipek Yton Ytukqio Xokk Suyez O Puyr Яжпюйвын Ырьнол Pijtu Reqenin Mugoq Burtukeg Sejomt Uneem Voekvo Oqonu Kebtregu
2017-06-24 - 2017-07-01	7	3	0	Piku Rfur Sejomt Uneem Voekvo Rogin Kajjoqq
2017-06-17 - 2017-06-24	21	5	4	Sejomt Uneem Voekvo Oqonu Kepunonre Uqodoc Gojnin Uqonu Mqehniregu Unujhujiu Raninu Jokvo Vqajytnog Unhen Qezujheg Uqod Jtrehin
2017-06-10 - 2017-06-17	31	12	1	Miokko xo Quyubo Xonij Exinereg Senuhtun Rip Урьчя Муроныня Pirtuiq Nireqjric Pukr Fuhjen Qcaxpiqu Reqeninu Vqoz Mkehememeg Supoj Joteen Mukr Sejomt Uneem Voekvo Jqugu Rekeqog
2017-06-03 - 2017-06-10	76	29	3	Ычуль Всурьнит Purjip Kuzinegiyt Pajhuwu Lupukaxxin Sejomt Uneem Voekvo Шысйун Чурысуш Caqiu Reqeninu Ukjonic Reqenin Урьчя Муроныня Xuniqu Uripeg Unhen Qezujheg Eqov Xaytreg Яжпюйвын Ырьнол Kajqun Jun Vqoz Mkehememeg Gquxijqug Zebtoxuc Sucjhokenepeaj U Qofij Jokvo Vqajytnog Pirtuiq Rip Unxkof Mcuhreg Pirtuiq Nireqjric Qcaxpiqu Reqeninu Xukiu Reqcurinu Qoe Uqodunxok Änvojqogä Zekij Qukcareg Цпыйлыт

Fig. 4. Temporal dynamics of relative reputation increment (“karma”) aligned with names of other users attracted by primary users’ posts enough to act towards them by commenting on posing “likes” or “votes” (actual names of other users are obfuscated because of privacy concerns).

Further, HTML reports produced by Aigents computational platform were available for use as part of Aigents web service as partially rendered on Fig. 3 and 4.

The value of positive reputation increment — called “karma” in context of [15] and this work — could be studied along the temporal axis aligned with the words attracting the most attention from other users acting towards the posts and comments containing these words, as it is shown in Fig. 3. In this example, it can be clearly seen that the maximum of 100% within the period is reached in the range between August 5th and August 15th in respect to posts on social topics of BICA-2017 conference (“bica”, “conference”, “social”).

The track of temporal dynamics of reputation changes could be also studied being aligned with valuation of other users based on extent of their contribution to comments, “likes” and “votes” in respect to posts of the primary user. In this example, it is clearly seen that most of the attention is earned during the period between August 5th and August 15th, given by 1 active user, to a less extent by 3 other users and, finally, by 20 poorly active users.

Given three hundred users acquired across five social networks, thirty users have been informally questioned in respect to applicability of the graphs and charts presented above. Most of them have expressed positive opinion in respect to usefulness of the results obtained. However, it has been found that use of private social networks such as Facebook, Google+ and VKontakte provides less precise and more biased view given the fact only the limited amount of data is available via the public API of these online services. On the contrary, the results obtained with community-owned social networks with no limits on data access, such as Steemit and Golos have provided more reliable and useful results, corresponding to natural expectations.

V. CONCLUSIONS

The approach and application designed, developed and tested as described above, seem practically applicable and useful for the purpose of tracking personal social dynamics and reputation in the context of day-to-day interactions of a user in social networks. Moreover, it seems useful to have connectivity patterns supplied with expression of emotional value, starting both with the most simple positive and negative sentiment evaluation associated with values of connectivity and reputation changes. The other direction of possible improvement could be a more precise assessment of reputation itself so it could be evaluated in relation to the entire community and not just personal history, — so the true opinion leaders can be figured out and the users may be able to track their own reputation development compared to the former.

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