Assessment of personal environments in social networks

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***Abstract*—The paper justifies importance of study of personal social environments in social networks, suggests practical metrics for its assessment, describes web application developed for this purpose and evaluates its practical applicability in different social networks.**

Keywords—data science; machine learning; personal data; social engineering; social network; text mining.

I. Introduction

Social networks are great instrument connecting people around the globe, enabling connectivity, escalating world-wide communications and powering social elevators. However, sometimes we can not benefit using them because we are not able to handle all connections properly, because there are too and average human is unable to handle all that “big data” coming through the social feeds. Also, in the course of communications, sometimes we barely make sense of actual impact of our own posts and likes. Both factors imply certain risks for any user of modern social networks - widely speaking, including any means of digital communications, as it has been discussed earlier [1].

Primarily, these risks are imposed by tightly interconnected society with its members interacting at high speed and high volumes in multi-agent manner, which leads to clustering effects in society [2] with risks of uncontrolled transformations of social structure and relationships within the society. Notably, the massive changes in social mood of psychological state of people can be synchronously instrumented by internet media and social networks in particular, as it has been shown in the independent works [3,4].

Practically, for each particular person, there could be two different kinds of danger considered and assessed: incoming – possibly induced from outer environment and outgoing – potentially caused by person themselves.

For the first kind, we can consider dangers of a) social engineering, such as fraud and unauthorized access; b) political manipulation, involvement in sects and illegal activities; c) impact on the part of mentally unhealthy or socially dangerous subjects.

For the second kind, there are d) actions that lead to the strengthening of the above-mentioned threats, such as involvement in social engineering, manipulation or exposure to influence; e) actions leading to long-term disruption of one's own social environment under temporary stress, such as insults to friends and colleagues; f) violation of existing legislation or ethical standards adopted in the community.

Here we discuss approach and practical solution to help people to make sense of their relationships on the Internet and in real time, figure out nature and temporal dynamics of these relationships and possibly draw conclusions beneficial for their safety and performance.

II. Approach and practical solution

To solve this problem, we are suggesting set of metrics used to assess personal social environment of a social network user. Accordingly to these metrics, users can build profiles of their interests, activity and connections to other people using online software service called Aigents and hosted at https://aigents.com/ Web site [5]. Using the service, users can make sense of themselves, their interests, words they say, things they like and friends and colleagues they have, including actual nature of relationships with them. This can be done by user granting the service access to any of supported social networks, assuming there is enough user data available. The latter depends not only on user's activity logged by network, but also by policy of given social network, restricting amount information available for analysis by external systems. Below is the list of profiles associated with respective metrics, as implemented at the moment, based on analytical approach described earlier [6].

My interests
Interests of my friends
Similar to me
Best friends
Fans
Like and comment me
Authorities
Liked by me
My karma by periods
My words by periods
My favorite words

My posts liked and commented
My best words
My words liked and commented
Words liked by me

The metrics for profiles listed above are calculated using two kinds of data.

First, there is data extracted from the original posts and comments and converted to feature vectors associated with the posts and comments [6]. The feature vectors are cleaned of commonly used words, such as articles and interjections, and are normalized on basis of relative popularity of the words, accordingly to dictionaries and frequencies of usage for given language – English or Russian. These feature vectors associated with posts and comments are further converted to feature vectors identifying particular users, their periods of activity on time scale and clusters of posts and comments representing topics of interest.

Second, there are relationships between the primary user and their friends and posts and comments of the both, assuming L_{ij} can be used to denote number of "likes" or "votes" other user j gives to posts and comments made by given user i and C_{ij} indicating number of comments user j makes in regard to posts/comments made by user i.

My interests – lists clusters of words identifying topics of groups of posts and comments associated by use of these words, either written by user or present in comments that user is identifying as "liked" or "voted" for. It is identified with adaptive clustering (with no number of clusters given in advance) where the lists of clusters and lists of features identifying them are built incrementally and simultaneously [7, 8].

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

Similar to me – ranks other users accordingly to *similarity* metric between each user and their connections calculated using feature vectors extracted from users' posts and comments [6] with normalized overlap between the two vectors evaluated as mutual similarity measure between users.

Best friends – ranks other users based on *friendship* metric which is symmetric strength of positive relationship based on value of mutual "likes" or "votes" between two users $L_{ij}*(L_{ji}+C_{ji})$, normalized by 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 – ranks users per *adherence* metric as strength of asymmetric or directed positive relationship, which can be evaluated as amount of "likes" or "votes" and comments that the other user is giving to posts of primary user. The metric is denominated by returned likes and comments, so that complete fan is one that pays more attention to primary user while the latter one pays 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 of denomination by mutuality of positive relationship.

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

Authorities – lists users accordingly to *authority* metric which can be also called "thought leader" or "opinion leader" or "the one that I listen to" which is the metric opposed to *adherence* as asymmetric positive relationship. It corresponds to amount of attention, i.e. number of "likes" of "votes", paid by primary user to other one, denominated by amount of attention (likes 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 of 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 user within given period t across set of periods T, normalized to the best achievement across all periods.

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

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

My words by periods – does the same with feature grouped by periods of time accordingly to dates of posts and comments. This profile makes sense to be assessed including *karma* metric discussed above, so the two can be correlated.

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

My best words – list of "words" used by primary user in own posts ranked accordingly to amount of "likes" or "votes" and comments these posts attract on behalf of other users.

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

The profiles and metrics described above are available for users of Aigents service at https://aigents.com/, in case if user grants the service access to any of three social networks, namely Facebook, Google+ and VKontakte.

In addition to support of "old style" social networks mentioned above, the service also supports "new school" social networks based on block-chain technology, namely Steemit at https://steemit.com and Golos at https://golos.io/. While there is no authorization support available to third-party services in those social networks, analysis of these networks can not be accessible to user of Aigents service. However, the analytics of selected accounts is being published at https://steemit.com/@aigents and https://golos.io/@aigents.

Also, besides being accessible by conventional interface on Aigents web site, the social analytics can be available via chat bots at Telegram as @AigentsBot and Facebook as “Aigents”.

More coverage of the matter is available at https://steemit.com/@akolonin resoure.

III. Discussion of results

Using the described metrics, for users that were explored, we have discovered patterns not obvious if using social networks in conventional way. Also, it has been observed, that quality and reliability of the assessment depend on amount of data logged by user's activity as well as extent of its availability accordingly to policy of given social network.

For the study and evaluation, we were not able to use most of user accounts for “old school” social networks, such as Facebook, Google+ and VKontakte, because of the privacy restrictions. So we evaluated results only for the users explicitly granting the right to publish the results. The other restriction imposed by these social networks is very limited access to user content and interaction history granted to automated analysis via official application programming interfaces (API) of these social networks. Effectively, for these networks, the analysis could be done only based on contents of “home page” of the user, including posts of the user themselves, “likes” these posts earn and comments are given to these posts by other users.

However, for “new style” social networks based on block-chain technology, such as Steemit and Golos, every piece of content and every user transaction related to content and other users are public by definition. So we were able to do complete analysis of any user including any of their posts and “votes”, (term used in place of “likes” conventional in the other networks) cross-referencing all users.

Grand problem with analysis of the “old school” social networks is pre-determined by restrictions they are imposing, making impossible to make sense of posts, comments and interactions involving user in groups and home pages and posts of the other users. That is, the accuracy and reliability of the results depends on amount of information contained in the home page and results may be constrained by its amount and get biased respectively.

On the contrary, the “new style” social networks are giving unlimited access to log of social interactions within the network. However, another problem has been discovered during analysis within these networks. Due to lack of verification of physical personal identity built into former networks, the latter ones exhibit substantial population of automated accounts (so called “bots”) performing automatic interactions which often makes no sense, like “voting” for a post, not having it actually read, and messing up the results. For instance, for some posts, the number of “votes” performed by “bots” was 10 times higher than number of human-made “votes”.

For the selected user, analysis of their activity in Facebook as been conducted and provided expectable results, like the following.

My interests – rendered few areas of interests, primarily scope of business interests of the user and their business domain.

Interests of my friends – discovered major cluster of users sharing interests of both of the former topics.

Similar to me – most similar users turned to be account of Facebook page associated with user's business plus brother of the user and two colleagues – one sharing scientific interests and other sharing business interests.

Best friends – the best friend of the user turned to be brother and the account of associated Facebook page with few close colleagues and friends the next.

Fans – the topmost friend turned to be again the account of Facebook page, then mother of the user and then one of his colleagues.

Authorities – the top authority position took well-known scientist conducting study in the area of interests of the user.

My karma by periods – the top karma has been earned by the user during the sick days with great amount of time spent on creating content for social network and attracting attention of the audience.

My words by periods – has turned to be render topics of activity over time in correct way, well correlated with *karma by periods*.

My favorite words, Words liked by me, My best words, My posts liked and commented – all profiles also gave verifiable and reasonable results.

For for other fews selected accounts on Steemit social networks, same analysis has been performed with results available under the following Web link, persistently public due to the nature of the Steemit social network: https://steemit.com/@aigents. The excerpts of the interpretation of the analysis for two selected users are cited below, with accounts identified by login nicknames following ampersand @.

Posts of @dantheman can be split in two groups: a) about block-chain, market, money and power; b) regarding voting and content.

People most similar to @dantheman on Steemit are @donkeypong, @son-of-satire, @dragosroua, @xeroc, @anotherjoe and @lukestokes - sharing concerns about "steem" and "people".

Best three friends of @dantheman are @tuck-fheman, @stellabelle and @krnel (this makes it surprisingly similar to @dan).

There is great fan of @dantheman called @johnathanhenry with may other following far away next.

The top authority for @dantheman is @steemitblog (no great surprise, huh) and then @larkenrose the next authority.

The most karma by @dantheman has been earned in August 2016, while addressing issues people using Steem for voting.

The most popular terms used by @dantheman are "steem", "people", "value" and "consensus".

The most liked posts written by @dantheman are "Why I Flag @ozchartart" this year and "Why do we fight to change the world?" and "Curation Rewards and Voting Incentive" last year and the words attracting audience of @dantheman to greatest extent are "people" and "means".

Posts of @son-of-satire, compared to previous accounts seem having more existential nature, less focused on one particular topic, so they can be split in four categories with the following (possibly speculative) interpretations: a) addressing questions "why?" regarding the "way of doing things"; c) regarding how to "give" and "keep"; d) concerning what is "wanted"; e) focused on matters connected to "steem".

Accounts most similar to @son-of-satire are @lifeworship, @dreemit, @trevor.george, @stellabelle, @j3dy, @riskdebonair and @the-ego-is-you, sharing interests regarding the "steemit", "people" and "time".

The ultimately best friend of @son-of-satire on Steemit is @thecryptofiend with @rigaronib, @dwinblood and @dreemit following at distance.

He has three consistent fans called @trans-juanmi, @selwi, @juliosalas and @jeff-kubitz. Ultimate authority for @son-of-satire seem to be @rubens9119, there are also @curie, @wowpeach and @steemsports but relationships seem to be more of mutual nature.

Most karma by @son-of-satire has been earned in February 2017.

Both examples above turned to be plausible and sensible in the course of verification by means of discussion within the network community.

IV. Conclusion And Future Work

Described service and suggested profiling metrics are intended for increasing level of self-awareness of a user while interacting with peers on social networks. It makes it possible to discover useful and beneficial relationships or even avoid possible threats and risks of social engineering. Functionality is available as web service at https://aigents.com/ with support for social networks such as Facebook, Google+, VKontakte, Steemit and Golos.

In the future work, we are planning to focus on application aspects of the approach and solution so it may turn practically usable of increase of personal performance and safety in course of online communications. The primary goals would be the following:

a) detection of so-called “bots” – either automated accounts or actual human users performing massive spamming operations manually;

b) detection of so-called “trolls” – communicating highly negative sentiment at large volume and high rate without of significant reason;

c) real-time detection of incoming social threats like social engineering – with illegal or politically biased intent;

d) real-time of outgoing social threats – spreading illegal content or performing socially destructive actions [9];

e) psychological modeling and evaluation of temporal dynamics of personal state for optimization of social performance [10].

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