Discover the Silver Lining Effect: Machine Learning Techniques for Learning User's Attitudes over Time on Social media

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1 Abstract

The way the users generate contents on social networks is descriptive of their affective state (e.g., personality, emotions, empathy). The analysis of the digital footprints left by users on social networks, known as *social media footprints* (e.g,. comments, likes, videos), is a very hot topic in the last decade. The proposed research will analyze such an information with the aim of detecting the user's typical attitudes. This will allow us to better profile user's social behavior, aiming to improve her satisfaction with personalized services. Specifically, we want to evaluate how user's positive attitudes spread during social events or, more generically, during discussions about social issues. Furthermore, this work will pay attention on how user's attitudes evolve over time w.r.t. external events.

2 Research domain

Users unconsciously spread footprints of their daily activities, moods and personalities everyday on social media. These signals are known as *social media footprints*. A social media footprint is the trail of data that is left behind by users on social network, and it is influenced by multiple factors. Understanding the way in which these contents are shared and their relative patterns is a very complex task, and we need to perform detailed analysis. The main scope is to offer better personalized services (e.g., item recommendation, personalized services, adaptive chatbots). In the last few years, there has been an increasing interest in considering user's attitudes inside social network platforms and their temporal evolution [2, 7]. These are related with user's activities inside social network. Our analysis will take into account the *silver lining* aspect of social network, in order to discover how user's positive attitudes spread during discussions about social issues (e.g., LGBT rights, vaccinations). The silver lining is defined in [3] as follows: "The silver lining effect predicts that segregating a small gain from a larger loss results in greater psychological value than does integrating them into a smaller loss". This concept could be applied also to the social network domain. The spread of bad contents should emphasize user's positive attitudes in the network, namely, the *silver linings*. Very often, social data analysis is focused on the detection of negative aspects of the network. Our approach

will focus on the spread of the *silver lining* of social network. As far as we know, there are no many contributions in this field. Brady *et al.* in [1] analyze how the presence of moral-emotional words in messages increases the diffusion of moral ideas in social networks. He defined this effect as *moral contagion*. Polignano *et al.* [5] propose an approach of empathy prediction developed with an algorithm of linear regression over Facebook's profiles. The main goal is understanding how to recognize persuasion in this topic and which users are more vulnerable to persuasion. Another question concerns if it is possible to promote ethic behaviors and positive influence in a social network domain. The study will be developed on social network platforms such as Twitter and Facebook. One of the challenges is the detection of the best low-level features (extracted from user's social signals) to predict user's behavior. Another challenge is how to consider temporal dimension of user's signals to understand changes in user's attitudes, and if it is possible to find behavioral patterns to detect weaker and more affected by persuasion users. For the analysis of a *silver lining* social effect, it is crucial to understand from social media footprints which features have a greater relevance for the good spreading of the message. This research wants to overcome some of these limitations, so it is guided by the following research questions:
RQ1: How to use social media footprints for understanding user's behavior over time?
RQ2 : Is it possible to find a correlation between low-level features of multimedia contents and user's high level attitudes?
RQ3: How to find behavioral pattern that could be used to an ethic personalization of contents?

3 Methodology

In this section, the main stages of the proposal are described. The method analyzes a generic social network system, that could be adapted to different social platforms. As in Figure 1, the problem could be divided in two sub-problems: (1) find user's affective state from features extracted from social media; (2) discover user's attitudes from her affective state and reactions. Since we are interested in temporal evolutions of user's attitudes, we have first to define a set $T = \{t_1, t_2, ..., t_n\}$ of time intervals and a set $E = \{e_1, e_2, ..., e_n\}$ of events. Let us denote a user's signal $s_u^{(t)}$ for a user u as a combination of multimedia user posts, that summarizes her activity in the network for a time interval t. Let us denote a user's affective state for a user u in an interval t as a vector $\boldsymbol{a}_u^{(t)}$. Each user's signal $s_u^{(t)}$ and each user's affective state $\boldsymbol{a}_u^{(t)}$ are characterized by a set of events E. Let us consider a generic user's signal $s_u^{(t)}$ related to the user u. For each post in the time interval t representative features will be extracted. We could distinguish between different categories of features, varying on the type of post that we are analyzing (i.e., text, image or video). Each affective state vector $\boldsymbol{a}_u^{(t)}$ for a user u at a time interval t, related to the semantic layer (or intermediate level) of our architecture, is builded upon several features

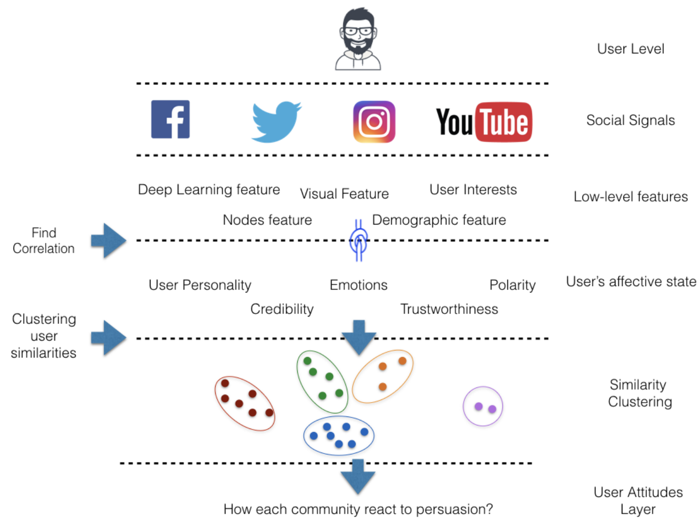

Fig. 1: General schema of the system architecture.

like *Personality* (modeled through the Big Five factors [4]), *Emotions*, *Polarity*, *Credibility*, *Trustworthiness* and *stylometric features*. The first task is to find a correlation between low-level features and the user's affective layer. The use of a dictionary gives us a discrete categorization of each user's affective state, but it could not find hidden relationships. Through clustering techniques, such as *k-means* , similar contents will be grouped, based on common features. Inferential statistics allow us to examine causal relationships between variables. With the use of multiple regression analysis we will separately predict every single parameter of each user's affective state. The results will enable us to provide a better prediction of the user's affective state, based on her social media footprints. The main objective of the second stage is the evaluation of the positive or negative impact that events have on the user's attitudes towards time. Social network is heavily affected by *persuasion*. Our scope is to understand which users are more persuasive for others and which users are mostly affected by persuasion. In addition, we would like to discover communities of fake cheerfulness and how to follow positive trends and moral contagion. The objective is to group users upon their affective state, in order to understand if it is correlated with her behavior towards persuasion. Our first step towards it is to group users based on their affective state vectors. For each user u, we will evaluate her similarity with others in terms of the features that described her affective state. We will define a set of communities C, named *affective communities*. All the communities are builded upon a topic q. The following step is the analysis of the evolution of a community towards the temporal dimension. The clustering among users with similar attitudes will provide us with the more predictive low-level and intermediate level features. As an example, we would like to take into account a community with particular features (e.g., community of extrovert people, with angry emotions, negative polarity and high authority) in two different temporal intervals t and $t+\delta$. We will denote such communities as $C_i^{(t)}$ and $C_i^{(t+\delta)}$. Community evolution could be seen as a sequence of events $e_1, e_2, e_3, ..., e_n$ that determine a change in the social structure of the community. The hypothesis that we would like to validate is that two users with similar attitudes will similarly react towards similar events. To this aim, we will evaluate the similarity between $C_i^{(t)}$ and $C_i^{(t+\delta)}$ and how the community evolves in the interval $[t, t+\delta]$.

4 Progress to date

Hitherto we have collected preliminary results on improving the prediction of a user's personality from low-level features, taken from images and videos. We have considered the PsychoFlickr dataset [6] from Flickr [1]. The analysis has been focused on detecting the correlation between visual features of high- and low-level extracted from images (through computer vision techniques and convolutional neural networks) and user's psychometric traits. At the same time, we have collected a video dataset, built with the 2016 movie trailers. The dataset has been enriched with explicitly (through BFI-44 questionnaire) and implicitly (through Apply Magic Sauce [2]) extracted personality traits of the users who watched the trailers. The results of the correlation analysis (see Fig. 2) are encouraging and demonstrate that there really exists a correlation among some low-level features and personality traits. As final step, we have found a correlation among low-level features extracted from videos and those extracted from images, connecting the two datasets through the users' personality traits. Currently, we are trying to determine a correlation between the user's affective state and the user's attitude over time in social network domain. The objective is to complete such a task as soon as possible, in order to test the two-side methodology on new data. To this end, we plan to use a dataset extracted from the MyPersonality application [3].

5 Evaluation and applications

We have to distinguish between high-level behavior prediction and user's affective layer prediction For the latter correlation, we will consider the measure of correlation between features extracted from images and videos and psychological traits (see Fig. 2). For user's attitude, we firstly have to evaluate the correlation between the user's affective state and the user's attitude inside the network. Furthermore, we will evaluate also the hypothesis about the correlation between the user's affective state inside the social network and her attitude inside the network. The communities will be evaluated in terms of classical metrics such as modularity, closeness and betweenness. We will also evaluate the influence of nodes inside communities in order to understand how the persuasion spreads

[1] https://www.flickr.com
[2] https://applymagicsauce.com/
[3] http://mypersonality.org

inside the network, tracking user's social activities, such as retweets, reactions to other user's post and replies to comments. Finally, for the evaluation task we

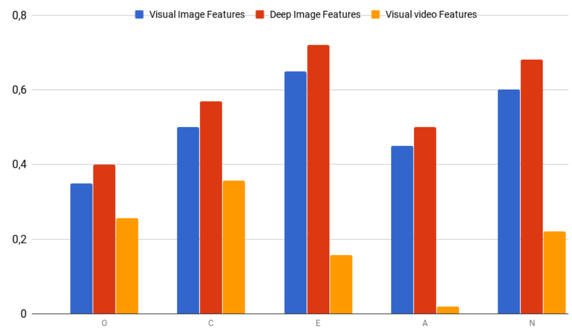

Fig. 2: Results of the correlation analysis.

will take into account also the temporal aspect of the user profiling. For this reason, we will apply a sliding-window approach taking snapshots along the user's timeline. For the evaluation of similarities based on the user's affective state we will use similarity measures such as the Pearson Correlation, Jaccard Mean Squared Distance and Cosine Similarity. The study of how the user's attitude evolves over time could have several applications. Among others, this could help achieve more accurate personalized recommender systems for services, public service advertising, and churn prediction.

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