Dynamic User-level Affect Analysis in Social Media: Modeling Violence in the Dark Web

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Abstract—**Affect represents a person's emotions toward objects, issues or other persons. Recent years have witnessed a surge in studies of users' affect in social media, as marketing literature has shown that users' affect influences decision making. The current literature in this area, however, has largely focused on the message level, using text-based features and various classification approaches. Such analyses not only overlook valuable information about the user who posts the messages, but also fail to consider that users' affect may change over time. To overcome these limitations, we propose a new research design for social media affect analysis by specifically incorporating users' characteristics and the time dimension. We illustrate our research design by applying it to a major Dark Web forum of international Jihadists. Empirical results show that our research design allows us to draw on theories from other disciplines, such as social psychology, to provide useful insights on the dynamic change of users' affect in social media.**

Keywords - Social media, Affect analysis, Persuasion, Social network analysis, Time dimension

I. Introduction

The term "social media" refers to internet platforms that allow the exchange of User-Generated Content (UGC). This includes various online communication platforms such as forums and blogs, content communities such as Flickr.com and YouTube.com, and e-Commerce communities such as eBay.com and Amazon.com [15][21]. Social media have attracted the attention of many researchers in recent years because activities such as product viral marketing [4] and social campaigns [9][28] can significantly impact individual behaviors. Playing a key role in this process is the concept of "affect," which is defined as a user's emotions toward objects, issues or other users. These emotions are induced by persuasions that users are exposed to during their use of social media, and in turn influence users' decisions such as purchase intensions [3].

Because of the important role that "affect" plays in social media, a significant number of studies have focused on affect analysis. Affect analysis is the evaluation of users' affect intensity. Previous studies on this topic, however, have largely focused on message level affect analysis, using various text-based features and classification approaches. Two important elements are missing from the extant literature. First, many studies ignore information about the user who posts the messages. Second, they tend to overlook the fact that users' affect may change over time. To overcome these limitations, we propose an innovative research design for affect analysis in social media by incorporating both user-level characteristics and the time dimension.

The rest of the paper is organized as follows. Section II reviews the advantages and limitations of text-based affect analysis, and introduces social psychological characteristics as an alternative way for affect analysis. Section III brings out the research gaps and the research question. Section IV introduces the basic components of our research design. In Section V we select an international Jihadi Dark Web forum as a testbed to demonstrate the effectiveness of our research design by conducting some exploratory regression analyses and hypotheses testing. Section VI concludes.

II. Literature Review

A. *Text-based affect analysis in social media*

Many studies on social media affect analyses focus on the message level, using text-based features and classification approaches. This line of research typically addresses two research questions. First, what text-based features can indicate affective expressions? Second, can we build a statistical model to automate affect analysis for text? For the first research question, researchers have proposed many text-based features to analyze affect. Subasic et al. [24] and Cho et al. [7] manually extracted lexical entries for affective words. Abbasi and Chen et al. [1] combined generic text-based features such as word n-grams, character n-grams and Part Of Speech (POS) tag n-grams with automated/manually extracted lexical entries for affective words. For the second research question, a number of classification approaches for affect analysis have been posted. Subasic et al. [24] adopted the fuzzy semantic typing approach, which assigns scores to each lexical entry as the probabilities of expressing predefined affects, and uses fuzzy logic to determine the most probable affect contained in the text. Cho et al. [7] analyzed affect by using a manually built classifier with natural language processing tools. Abbasi and Chen et al. [1] developed a Support Vector Regression (SVR) classification approach, which uses manually coded training dataset to train

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the SVR classifier, and then applies the trained classifier to the whole dataset for affect analysis.

These text-based affect analyses have two major advantages. First, the process of affect analysis can be partially automated, such as the extraction of text-based features, the training of classifiers, and the evaluation of affect intensity of the text. Second, this approach allows us to extend affect analysis to multi-language contexts, because the use of generic text-based features (such as n-grams) is not confined to English [1]. Yet, there are important limitations to this approach: it ignores information about the user who posts the messages, and it overlooks the fact that users' affect may change over time in the presence of persuasions [29]. Our new framework provides a much richer framework for dynamic affect analysis.

B. *User-level affect analysis in social media*

As mentioned earlier, affect is defined as a person's emotions toward objects, issues or other persons [22]. There are two generic types of emotions [24]. The first type of emotions, or "positive affects," includes amity, humor, and peace. The second type, or "negative affects," includes anger, horror, and violence. Meanwhile, the intensity of a positive/negative affect can be described using a score between 0 and 1 [1][24]. Social psychology theories suggest that the change of a user's affect is not only related to the persuasions from others [11][22], but also the user's own social psychological status [8].

Persuasions influence users' affect through two ways: the intensity of persuasions and the volume of persuasions [22]. Petty et al. [22] demonstrated that persuasive messages with stronger affect intensity have more persuasive power. Petty et al. [22] also showed that although a moderate number of repetitions of persuasive messages may increase the persuasive power, an excessive number of repetitions of persuasive messages may reduce the persuasive power.

In the context of social media, the intensity of persuasions can be measured by the average affect intensity of the persuasive messages a user faces, which can in turn be quantified using text-based features and the machine learning approach, as proposed by Abbasi and Chen et al. [1]. The volume of persuasions can be measured by the total number of persuasive messages a user faces.

On the other hand, a user's own social psychological status is also a strong predictor of his/her future affect. A user's social psychological status can be measured on two dimensions: the user's original affect, and the user's social status among others. A user's original affect, including those positive and negative, are both self-enhancing. For example, a user with positive affect will seek positive messages, which in turn further enhance his/her positive affect [29]. The same logic applies to negative affect [10]. A user's social status among others can be used as an indicator for the similarity of affect between the user and others. For example, users who share similar affect with others in a social network also tend to be better connected in the network [29]; while isolates (users who are outside of cliques) are likely to be individuals whose affect is different from others'.

A user's original affect can be measured by the average affect intensity of the messages that the user posts [1]. To measure a user's social status among others, there are two alternative approaches. The first is to measure the average length of threads in which the user participated [2]. For example, if the average length of threads that a user participates in is high, it indicates that the user can maintain active communication with others. It is then likely that the user may have similar affects to others' [8]. On the other hand, if the average length of threads that a user participates in is low, it indicates that the user can hardly maintain communication with others, suggesting that his/her affect may be very much different from others [8].

A second way to measure a user's social status among others is through Social Network Analysis (SNA). A social network in social media can be constructed as a directed graph based on the reply-to relationship between users [19][30]. The nodes represent social media users, and the links represent reply-to relationships. More specifically, if B started a thread, and A replied to this thread, then there will be an arc pointing from B to A. Examples of prior research on social media using SNA include the Bulletin Board System (BBS) topology analysis by Kou et al. [19], role detection in online discussion groups by Fisher et al. [12] and Welser et al. [27], as well as the analysis of Word Of Mouth (WOM) effect in online markets by Brown et al. [4]. The structural attribute of a node can be measured using many different centrality metrics, and the most popular ones include: (1) degree centrality, which is a tally of the number of links incident upon a node; (2) closeness centrality, which measures how close a particular node is to all other nodes in the social network; and (3) Freeman betweenness centrality, defined as the proportion of the shortest paths between any pair of nodes that pass through the interested node [13]. In other words, Freeman betweenness can describe the power of a node in controlling the communications between other nodes. Among these centrality metrics, betweenness centrality has been demonstrated to be a good measure of the role of a person in the social network [16]. In a network of social media users, with similar affect, they are more likely to engage in frequent communications. Hence, the Freeman betweenness of users inside the "clique" will be low [8]. Conversely, if the Freeman betweenness of a user is high, it suggests that the user is isolated from cliques and has only limited communications with other members, which in turn indicates that the user is not likely to share similar affect with other social media users [8].

C. *Research design for dynamic analysis*

Previous studies on text-based affect analysis rarely considered the time dimension [1][7][24]. However opinions diffuse through social network over time [25], and a user's affect may change accordingly. It is a natural extension of social media affect analysis to incorporate the time dimension.

Several studies have considered the time dimension, including studies of both social media and real world. Examples include predicting link formation in an email communication network [18], predicting link formation in a criminal network [14], and predicting the probability of a patent being cited by using a co-authorship network [16].

These studies take time dimension into account by using time-dependent design.

Time-dependent design typically includes two steps: longitudinal data collection and time-dependent feature representations. Longitudinal data collection means features are collected over time [18]. There are two choices for time-dependent feature representations: using either a time spells approach or a sliding windows approach. The time spells approach divides the entire span of sampling time frame into equal, sequential, and non-overlapping spells of time. Then it calculates the average value of each feature for each user in each of these spells [16]. An alternative is the sliding windows approach, which creates overlapping time periods across the sampling time frame, and calculates the features in the same way with time spells approach [18]. The time spells approach is chosen over the sliding windows approach in this study because the empirical model interpretations are much less intuitive when spells overlap with each other.

III. Research Gaps and Research Question

The discussions above show that the existing broad literature on social media affect analysis present two prominent research gaps. First, it has thus far neglected useful information about the user who posts the messages. Second, it has largely overlooked the time dimension, where affect may change over time. Hence, the research question we address in this paper is:

Can we incorporate time and user-level characteristics into affect analysis, so as to better understand the dynamic changes of "affect" in social media?

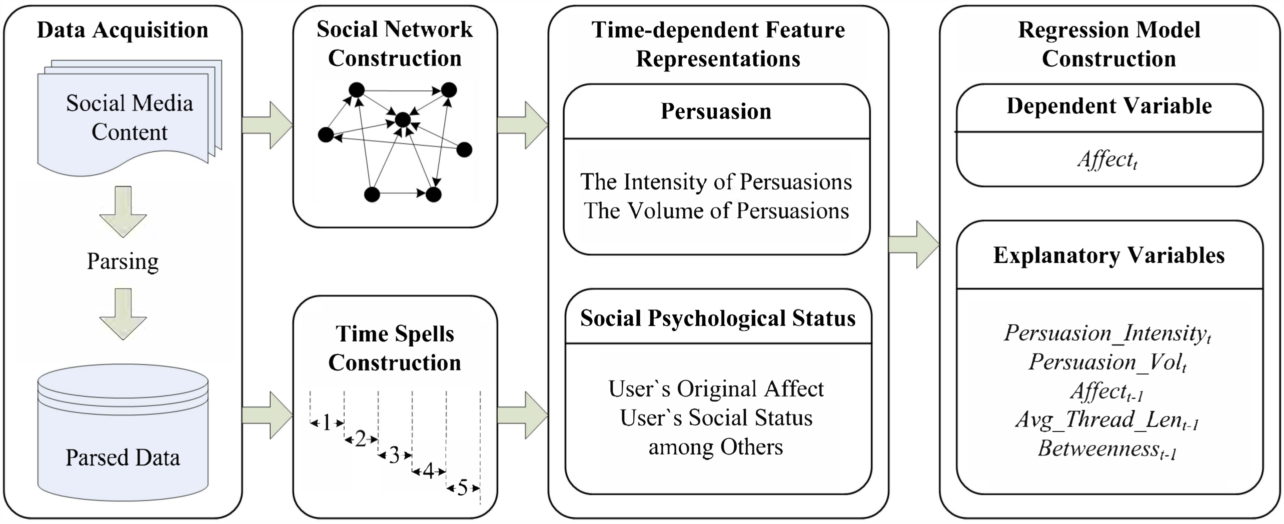

Figure 1. Research design diagram

IV. Research Design

The research design diagram is shown in Figure 1 and contains five components: data acquisition, social network construction, time spells construction, time-dependent feature representations, and regression model construction.

Social media content is spidered in raw format, such as HTML. Message content and meta-data are then parsed out from the raw data and stored in the database.

The social network is constructed in an accumulative manner by adding nodes and links based on the thread structure over time.

We represent time-dependent features in several ways. The user's affect intensity, the intensity of persuasions, and the length of threads that a user participated in, are calculated as their average values for each user in each time spell, respectively. Volume of persuasions is measured as the total number of messages visible to each user in each time spell. Also for each user in each time spell, we calculate "Freeman betweenness," a metric that describes the user's role in the social network of reply-to relationships. We consider the snapshot of the social network at the end of each time spell.

To construct regression model, we use each user's affect in each time spell as the dependent variable, and we select explanatory variables by drawing on the literature of social psychology and social networks.

V. Data Analysis and Discussions

A. Testbed Description: Dark Web and Violence

We demonstrate the effectiveness of our proposed research design by using a "Dark Web" online testbed developed by the Artificial Intelligence Lab of the University of Arizona [6]. We choose the AlFirdaws forum, which is a large international Jihadi forum, as the experiment testbed, and we choose violence, which is a negative affect, as the selected affect.

The Dark Web includes social media that are run, supported and used by extremists for purposes such as propaganda, communication, and inciting violence [23][26]. Social media such as web forums have become popular tools for extremists because they are cheap and efficient ways to reach a large audience and to sway public opinions [17]. Monitoring and analyzing the Dark Web is important because it may allow us to better understand how users interact and engage with each other in conversations, and whether and how violent intents may spread from user to user.

The AlFirdaws forum supports Jihadi movement and has been used as a testbed for affect analysis by previous studies such as Abbasi and Chen et al. [1]. A summary of the statistics of the AlFirdaws forum is shown in Table I.

TABLE I. SUMMARY STATISTICS OF THE ALFIRDAWS FORUM

Statistics	Value
Data range	2005-2007
Time span	1,068 days
Total number of users	1,771
Total number of threads	7,575
Total number of messages	31,019
Average thread time span	27.37 days
Average thread length	4.095 messages
Average number of messages per user	6.187

Forum pages are spidered in HTML format and the following data are parsed out: content, such as message and message ID; time stamp, such as posting date and time (year, month, day, time); user, such as user ID and user screen name; and content structure, such as thread title and thread ID. As a result, the messages we collected from the AlFirdaws forum were posted over a three years span (2005~2007, 1,068 days in total). There were 1,771 users registered and posted messages during these three years. They started 7,575 threads, and posted 31,019 messages in total. On average, each thread lasted for about 28 days and contained about 4 messages, and each user posted roughly 6 messages.

We choose each day as the basic time unit [18]. Since the average time span of a thread is 27.37 days, we selected 28 days as the width of the time spell, so that it is likely to cover an entire thread on average. Given 1,068 days in total and a width of 28 days, this resulted in 39 time spells for our analysis.

In our research we assume that if a user participates in a thread, then he/she is exposed to all prior messages at the time that he/she replies. Those prior messages can be used to derive metrics that represent persuasions from other participants of the forum.

B. Hypotheses Construction

Our first set of research hypotheses (H1) delineates the relationship between a user's violence level and the persuasions the user faces. Social psychology studies demonstrated that stronger intensity of persuasions may increase the persuasive power [22]. Since the AlFirdaws forum attempts to incite violence [23], messages in our testbed are expected to contain the violence affect. Thus we expect that a user's violence level is positively correlated with the intensity of violence of persuasions (*Persuasion_Intensity*) a user faces.

H1a: The intensity of violence of persuasions faced by a user is positively correlated with the user's violence level.

According to social psychology literature, an excessive amount of repetitions of persuasions may reduce the persuasive power [22]. Persuasions in our testbed could be excessive, because in Dark Web social media, users debate various topics relate to religious and politics, which involve repeatedly expressing ones' opinions [26]. Thus we expect that a user's violence level is negatively correlated with the volume of persuasions (*Persuasion_Vol*) a user faces.

H1b: The volume of persuasions faced by a user is negatively correlated with the user's violence level.

Our second set of research hypotheses (H2) is concerned with the relationship between a user's violence level and the user's social psychological status. It was demonstrated that a user with negative affect is more susceptible to negative persuasions; so the negative affect of the user tends to be self-enhancing [10]. Therefore we hypothesize that a user's violence level is positively correlated with the user's original violence level (*Violence*).

H2a: A user's violence level in an earlier time period is positively correlated with the user's violence level in future time periods.

In terms of a user's social status, the average length of threads that a user participates in represents the communication patterns of the user with others [2]. The average length of threads that a user participates in is longer if the user can maintain communications with others. On the other hand, the average length of threads that a violent user participates in may be shorter because he/she may share very different affect intensity with others [8]. Therefore we hypothesize that a user's violence level is negatively correlated with the average length of threads (*Avg_Thread_Len*) that a user participates in.

H2b: The average length of threads that a user participates in an earlier time period is negatively correlated with the user's violence level in future time periods.

The Freeman betweenness reflects the role of a user in the social network [16]. A user would have higher betweenness if he/she is isolated from cliques, and would have lower betweenness if he/she is a member of a clique [13]. On the other hand, violent users are more likely to be isolates rather than being inside cliques, because thay may share very different affect with others so that it is more difficult for them to maintain communications with others. Hence, we hypothesize that a user's violence level is positively correlated with the Freeman betweenness (*Betweenness*) of the user.

H2c: A user's Freeman betweenness in an earlier time period is positively correlated with the user's violence level in future time periods.

C. Regression Model and Regression Sample Construction

We construct the following regression model to test the above hypotheses. α and β are regression coefficients of the explanatory variables of persuasions and a user's social psychological status, respectively. The subscript i denotes the ith user, and the subscript t the tth time spell. c is the intercept, and ε is the error term.

$$
\begin{aligned}
Violence_{it} = c &+ \alpha_1 Persuasion\_Intensity_{it} \\
&+ \alpha_2 Persuasion\_Vol_{it} \\
&+ \beta_1 Violence_{i(t-1)} \\
&+ \beta_2 Avg\_Thread\_Len_{i(t-1)} \\
&+ \beta_3 Betweenness_{i(t-1)} \\
&+ \varepsilon_{it}
\end{aligned} \tag{1}
$$

To reduce the skewness of the data and approximate the assumptions of the linear regression model, we take the logarithm of *Persuasion_Intensity* and *Persuasion_Vol*, as well as the inverse of *Avg_Thread_Len* and *Betweenness* before incorporating them into the regression model.

We restrict our analysis to active users (non-lurkers) of the forum only. Lurkers are forum users who post occasionally or not at all [20]. According to Chen [5], up to 90% of the users in online communities are lurkers. Since lurkers seldom post messages, there are not sufficient data to analyze the relationship between their affect and other variables. We therefore remove lurkers from our regression sample. To do this, we first rank users of the forum by the total number of messages in descending order in our dataset, and then retain only the top 10% of users.

D. Regression Results and Discussions

TABLE II. REGRESSION RESULTS (ADJ-R^2 = 83.28%)

Variable	Coef.	Std. Err.	t	p > |t|
log(*Persuasion_Intensity$_t$*)	+0.656***	0.041***	+15.87***	0.000
log(*Persuasion_Vol$_t$*)	-0.010***	0.002***	-4.84***	0.000
Violence$_{t-1}$	+0.371***	0.035***	+10.66***	0.000
(*Avg_Thread_Len$_{t-1}$*)$^{-1}$	+0.133***	0.043***	+3.09***	0.002
(*Betweenness$_{t-1}$*)$^{-1}$	-0.072*	0.038*	-1.91*	0.057

Note: *$p \le 0.1$, **$p \le 0.05$, ***$p \le 0.01$

Table II shows the regression results. The regression coefficient on the logarithm of the intensity of persuasions is positive (+0.656) and statistically significant ($p < 0.01$), which supports the hypothesis (H1a) that the intensity of violence of persuasions is positively associated with a user's violence level [22]. The regression coefficient on the logarithm of the volume of persuasions is negative (-0.010) and also statistically significant ($p < 0.01$), suggesting that the volume of persuasions is negatively associated with a user's violence level. According to Petty et al. [22], a moderate number of repetitions of persuasions may increase the persuasive power; however an excessive number of repetitions of persuasions may reduce the persuasive power. This result is consistent with our hypothesis: due to the nature of the Dark Web, there is excessive volume of persuasions in the AlFirdaws forum; therefore, an increase in the volume of persuasions will be associated with a decrease in users' violence level.

We now turn to the relationship between a user's social psychological status and his/her violence level. The regression coefficient of a user's original violence level is positive (+0.371) and statistically significant ($p < 0.01$), which supports hypothesis (H2a) that the violence level of a user tends to be self-sustaining and increase over time. The regression coefficient of the inversed user's average length of threads is positive (+0.133) and significant ($p < 0.01$), which indicates that if a user can maintain communication with others in a thread, or the thread the user starts attract more repliers, then the user tends to be relatively mild. This result is consistent with the hypothesis (H2b) that a user is likely to be less violent if the threads that the user participated in are relatively longer. The regression coefficient of the inversed user's Freeman betweenness is negative (-0.072) and statistically significant ($p < 0.1$). This is also consistent with our hypothesis (H2c) that a user who has low Freeman betweenness is less likely to post violent messages. In all, both Hypothesis 1 and Hypothesis 2 are supported, as summarized in Table III.

TABLE III. SUMMARY OF HYPOTHESES TESTING

Hypothesis		Coef.	Supported / Not Supported
H1	H1a (the intensity of persuasions)	+0.656***	Supported
	H1b (the volume of persuasions)	-0.010***	Supported
H2	H2a (user's original violence level)	+0.371***	Supported
	H2b (the average length of threads)	+0.133***	Supported
	H2c (user's Freeman betweenness)	-0.072*	Supported

Note: *$p \le 0.1$, **$p \le 0.05$, ***$p \le 0.01$

We further consider the explanation power of the proposed statistical model. According to the adjusted-R^2 (83.28%), our model explains 83.28% of the variance of the dependent variable, indicating a satisfactory fit.

The regression results discussed above provide several new insights on the change of users' violence in Dark Web forums. In these forums, persuasive messages framed in a violent tone may attract more violent users. All else being equal, the continuous participation of a user in the Dark Web forum may lead to increase violence over time. If a user's threads attract few replies, or if discussions stop after the user participates in the threads, those threads will be shorter. This may indicate that the user is more violent than others. If a user tries to participate in others' discussions but is isolated from the cliques of the online social network, the user's Freeman betweenness would be higher; this may also indicate that the user is more violent than others. These insights will not have been available had we not incorporated user-level characteristics as well as the time dimension into our analyses.

VI. CONCLUSIONS AND FUTURE DIRECTIONS

In this study, we proposed an innovative research design for affect analysis in social media. There are three major contributions in this work. First, we incorporated user-level characteristics in addition to text-based affect analysis. Second, we used social network analysis to derive metrics that represent the user-level features, such as a user's social status in social media. Last but not least, we integrated the time dimension into the analysis, and examined the dynamic change of users' affect over time.

We tested the proposed research design on a Dark Web forum. Statistical analysis results demonstrated its effectiveness and highlighted new insights on the dynamic change of users' affect in these forums.

There are several directions that our current work can be extended. First, in addition to the use-level characteristics that we discussed in this paper, it will be interesting to identify additional features that may be used for affect analysis. This includes demographic information about users available on some forums but not on our testbed. Second, our research design may be easily extended to other types of social media, such as blogs, micro-blogs (e.g. Twitter.com) and content communities (e.g. YouTube.com). Third, our proposed research design may also be applied to analyze other affects or emotions, as appropriate in other contexts.

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