

The computational mechanics approach in analyzing emotion contagion on social media.

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Introduction

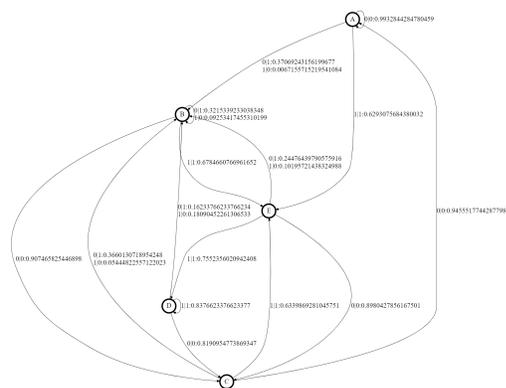
Social media platforms providing online discussion platforms act as medium for users to share, discuss, and shape their opinions within a community. These communities are comprised of users from different demographics yet having common interest come together to discuss various issues. Furthermore, social media platforms give them an opportunities to learn new information and understand others perspective around the issues.

Despite the growing popularity of social media platforms like Facebook, Reddit, and Slashdot, these platforms often struggle to provide a constructive discussion climate due to the proliferation of uncivil behaviors polluting discussion climate (Anderson & Huntington, 2017; Cheng et al., 2017; Hannan, 2018). Anti-normative behaviors root from: user-side (socio-political orientation & ideologies, level of knowledge, personal experience) and platform-side issues (platform affordance, lack of means to enhance social presence and social cues and self-regulation). Issues emerging due to the prevalent uncivility on social media platforms often derail discussions affecting user experience and discussion quality. These anti-normative behaviors often are the byproduct of user's emotional states (Kramer et al., 2014). Therefore, these behaviors can be contagious as past studies have shown that exposure to others emotion on social media leads to emotion contagion. Here, the emotion contagion is defined as "the tendency to automatically mimic and synchronize expressions, vocalizations, postures, and movements with those of another person's and, consequently, to converge emotionally" (Hatfield et al., 1993).

This project focuses on understanding user-side issues to know how user's own past negative sentiments and as well as other's past negative sentiments influence their behavior on social media platforms. These behaviors are dynamically reflected through users comment on social media platforms. Using these behavioral traces, we can use stochastic process to predict and gain insights into human behaviors. The behavioral feature we are interested in is negative sentiment. The goal of the study to understand negative sentiment contagion through 1) once own past behavior, and 2) other's past behavior.

The project aims to build computational landscape of user's behavior collected from reddit as one of the instances of social media. The use of social media sites' APIs has made it possible to collect user's digital traces left in the form comments and reactions. Using this specific dataset along with Natural Language Process (NLP) techniques, we can code, and label emotions and sentiments as expressed by the user about different occasions. Depending on the tool used to code, the content is labeled with various types of emotions and sentiment scores, from this point the creation of different time series for each comment will be created.

My aim for this project is understand any apply dynamical system theory to social networks present online which often are the realization of our offline networks. The focus has been to build a minimally complex and maximally predictive computational model to investigate negative sentiment contagion online. First autoregressive model focus on user's own past behavior to predict their future behavior. We use a machine which is a unified hidden Markov



ure behavior. we use ϵ -machine which is a universal hidden Markov predictive statistic of the past to predict future of a conditionally s. In another words, the emotional behavior of users at time t is can behavior at time $t-1$.

ject also aims to build alternative autoregressive model suggesting not limited to user's own past action but also on past action of their del, we need a parallel time-series to indicate the social influence of it user's own past behavior time series and social influence time series predict the present behavior through this model (epsilon-transducer). nt to the user comment as either their own past behavior if it was influence if there are replying to someone else comment.

This project is inspired by Darmon's (Darmon, 2015) work who applied dynamical system theory to social systems. Similar to his work, Causal State Splitting Reconstruction (CSSR) algorithm will be applied to these two proposed models. We identify the predictive states and distinguish between them if they have similarity less 0.001.

In the following sections we first delve in the past literature around emotion contagion on social media to highlight emergent themes and theoretical gaps which this study aims to fill. Then the paper further explains the methodology, results and important insights from our case study of reddit dataset.

Literature Review

Emotions and Sentiments

Despite years of research in the field of psychology, there is no consensus on the definition of emotion. However, American Psychology Association (APA) define emotion as 'A complex pattern of changes, including physiological arousal, feelings, cognitive processes, and behavioral reactions, made in response to a situation perceived to be personally significant'. Another similar definition comes from Thoits' (Thoits, 1990) who points out at 'the four interconnected components: (1) situational cues, (2) physiological changes, (3) expressive gestures, and (4) an emotion label that names the specific configuration of components.' Both definition highlights the multidimensional aspect of emotion including physiological symptoms as well as our thoughts and feelings often expressed in different modalities such as facial expressions, postures, and words. Notably, both definitions also have all the components of sentiment.

One of the earlier definitions of sentiment comes from Cooley (Cooley, 1921) who referred to sentiment as "By sentiment I mean socialized [my emphasis] feeling, feeling which has been raised by thought and intercourse out of its merely instinctive state and become properly human. It implies imagination, and the medium in which it chiefly lives is sympathetic contact with the minds of others." Notably, this definition indicates the social aspect of sentiment. Later, Gordon (Gordon, 2017) further distinguished emotion and sentiment by defining sentiment as "socially constructed pattern[s] of sensations, expressive gestures, and cultural meanings organized around a relationship to a social object". In his writings Gordon supported the definition of emotion provided by Thoits and argue that sentiment not only involve the four components of emotion but also one additional component of sociality. The socially constructed meaning of emotion involving the social object makes the sentiment distinctly social. Owing to the similarity in emotions and sentiments they are often used interchangeably, and we refer to them as emotion in this paper. To experience an emotion, one must experience all four components as well as should have socially shared meaning attached to it.

The definition provided by Gordon et al. (Gordon, 2017) also indicate the cognitive processes involved in the "appraisal" of the emotional state occurred due an event or situation. According to appraisal theory (Scherer, 1999) emotions are the product of cognitive process evaluating the situations or event whether it is potentially harmful or beneficial to the individual.

Emotions are triggered as a response to the initial stimulus. It is important to note that the intensity of emotion experience as well as our response depend on various representation of the initial stimuli and our attention to it i.e., emotion induction. Attention involves our engagement with the stimulus leading to the activation of certain cognitive processes which further leads to sharing. In another words, the more attention we give to the social object the more we think about it and more likely share our thoughts about it with others. In addition, the amount of arousal induced by emotion also influences this sharing behavior which has been illustrated by Codispoti et. al. (Codispoti & De Cesarei, 2007) in their study i.e., emotion such as anger induce high level of excitation and are highly likely to increase the sharing tendencies. Hence, we can say that emotion is not purely a personal experience and involve interpersonal element to it.

The emotion influences our interpersonal communication. While interacting with others we often react to the social cues provided by our counterparts. Often our reaction based on emotional evaluation of the messages we receive due our limited capacity of cognitive information processing (Lang, 2017, p. 4). There are studies (Brody, 2009, p.15) investigating emotion as motivational system involving physiological, cognitive, behavioral and experiential components evaluated either positive or negative valence which arise during interpersonal situation and events. We tend to pay attention to these interpersonal situations as they influence our state of well-being. Another classical study conducted by Schachter and Singer (Schachter & Singer, 1962) revealed that emotions having “real” underlying physiological substrate is shaped by our social interpretations which are subjective, or variable induced through social interaction. Hence, emotions are as embedded component of interpersonal relationships which acts as mediator, moderator or sometimes consequences of our message interpretations during interpersonal interactions.

The role of emotions is not limited to interpersonal communication as we also see the emotions influencing group communicative processes. According to Turner et. al. (Turner & Stets, 2005) emotion is the energy which sustain or change the communities or societies. Moreover, emotions play a motivational role which has the significant role influencing social structure and culture of the society. The transmission of emotions, from a diffusional perspective, negative emotions are shown to be more contagious acting as a popular mechanism of spreading misinformation [citation]. One study (Burki, 2019) investigating the effect of agenda setting in influencing twitter sentiments in 2016 US presidential election found that a greater number of intermedia influences were identified on negative than positive sentiment contagion. Furthermore, another study (Burki, 2019) investigating the misinformation diffusion around covid-19 found negative sentiment one of the prevalent mechanisms of misinformation diffusion leading to fast and large-scale diffusion compared to positive sentiment. Along these lines, different studies (Christophe & Rimé, 1997; Curci & Bellelli, 2004; Harber & Cohen, 2005) reveals that people are more likely share stories having emotional content, moreover, that people’s decision to propagate information on the social networks highly influenced on emotional selection rather than information (Rimé, 2017). Owing to the effect of emotions on our social network structure and order, it is important to investigate emotion as an independent source affecting how its manifestation emerging at micro level in the society generate or guide change at macro level in the social structure and culture.

RQ1: Are there any hidden patterns in individual’s negative sentiment expression on social media?

RQ2: Do we see negative sentiment patterns at macro level replicating the micro level behaviors on social media?

Complex human behavior

Users’ behavior on social media can be described as complex system which can be represented as nonlinear dynamical systems. We adopt computational mechanics approach using stochastic models and statistical tools to investigate negative sentiment analysis on social media. The computational mechanics tools have been used to model time series as well as input-output systems (Shalizi, 2001; Shalizi & Crutchfield, 2001). Social media platforms are dynamic in

systems (Shanazi, 2001, Shanazi & Crutchfield, 2001). Social media platforms are dynamic in nature as they are based on users' social network. They often resemble users' offline network (Subrahmanyam et al., 2008; Subrahmanyam & Greenfield, 2008) where users are represented by individual nodes and the relationship between them are edges. Dynamicity is also reflected by the flow of emotions within these networks. One's emotional state within the network can influence other's emotional states which relate to the node/user expressing their emotions on these platforms. However, to what extent these emotions are predictive to system's future states and how does community characteristics such as norms, rules, and platform affordances influence these emotions are open question. The project is one present computational mechanics approach in investigating these questions. Notably, long term goal of the project is to investigate the earlier presented research questions for multiple platforms such as YouTube, Reddit, and Facebook. However, for the class project I present a case study for the reddit dataset with the developed pipeline which can be extended for the rest of the platforms.

Methodology

Dataset and Time series generation

To address the research questions posed earlier the project takes the case study of social media behaviors using reddit's comment from political subreddit. Selection of political subreddit was because political discussion are often overridden with sentiments and emotions. The dataset of 15,558 post-comment (post and the first comment on the post) pair was collected on May 17, 2018 of 15 most active reddit users from the hundred most popular posts in the subreddit. The dataset covers comment for the duration of 11 years from 2007 ~ 2018. To generate sentiment score, we used IBM Watson Natural Language Understanding tool which generate positive or negative sentiment score based on the negative or positive valence expressed in both post and the comment. Since, the project investigate negative sentiment expression patterns our variable of interest was sentiment score. All the post-comment pairs were evaluated assigning values between -1 and 1 where negative sentiment was score between -1 to 0 and positive sentiment ranges from 0 to 1.

Keeping the deliverable for the project in mind, I only analyzed half of the dataset having 5 active users. After the sentiment score generation, the scores were aggregated per hour resulted with 5 time series representing negative sentiment expressions for the five users per hour. Then we recode the sentiment score for both individual's own comments as well as the original post representing social influence. Here the unit of analysis was individual user. However, I also analyzed overall community behavior by creating time series of all the comments. Since, I was interested in negative sentiment the recoding scheme is represented by equation 1 and 2 where represent user's own negative sentiment expression (1 when the sentiment score is negative, 0 otherwise) and represent social influence/input generated using original post (1 when the sentiment score is negative, 0 otherwise). There are total six time series generated this way (5 time series representing each individual and one for the aggregated community behavior).

Model parameters

To build equivalence relation to define e-machine we require the knowledge of the full predictive distribution. However, the predictive distribution is not known in advance hence we need to infer the e-machine using some statistical procedure. Therefore, we used Causal State Splitting Reconstruction (CSSR) algorithm (Darmon, 2015; Crutchfield & Young, 1989) to find the estimator for the e-machine associated with a realization of the observed process by splitting

candidate causal states. Once we have the approximation for ϵ -machine we can further build the transducer by providing the social influence as input to the transducer to predict user's behavior. Considering that the majority of the comments are not replying to the same parent post, we distinguish among predictive states if they have a similarity less than $\alpha = 0.001$, we go two time-steps into the past to make predictions, $L_{\max} = 2$, and $\tau = 1$ hour as the $\{X_t(v), Y_t(v)\}$ captures the daily behavioral pattern of the user.

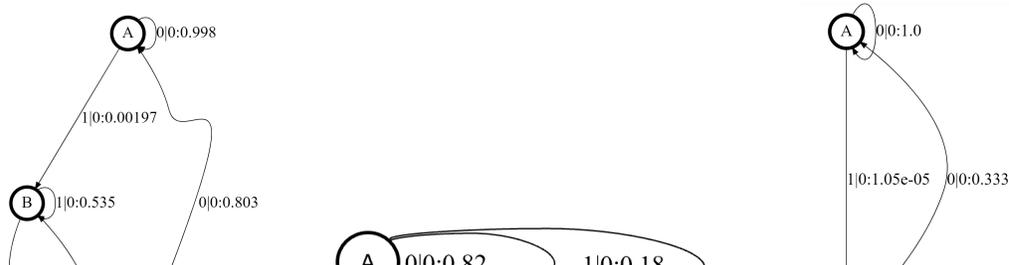
Results:

Figure 1: the a) epsilon-machine, and b) transducer representing community's negative sentiments

First, I present macro level behavior representing aggregated community behavior (Figure 1). Notably, number of predictive states in an ϵ -machine represents the approximate reflection of user's behavior. It seems that community level ϵ -machine is little less complex than the transducer as we observe 4 predictive states for the ϵ -machine and 5 for the transducer. Hence, we can say that by providing social influence input the model can sufficiently predict user's negative sentiments, however, their behavior is haphazard predicted as symbolized by the complex architecture of the transducer. Similarly, for individual users we find three types of behavioral patterns.

Considering individual behavioral patterns, we observed three types of ϵ -machines with one, two, and three predictive states. The most complex model having 3-states indicate that self-driven behaviors are not much complex which suggests that user switch from negative to non-negative sentiment states and vice-versa. On the other hand, 1- state ϵ -machine indicate that the user's behavior is random similar to the fair coin, however, not the fair coin. Since, we just have one state the statistical complexity (C_μ) for this model is 0.

Moving on to the epsilon-transducer we observe two kind of patterns: 1) extremely complex with 7, and 8 predictive states, 2) extremely simple with 1, and 2 predictive states. The simple epsilon-transducer models are analogous to the ϵ -machines. For the complex epsilon-transducer models, it seems that knowledge of past social influence can affect user's behavior much more complex leading to higher statistical complexity. It seems that user's own past negative sentiments guide their behavior, however, adding social influence shows much more hidden complex patterns.



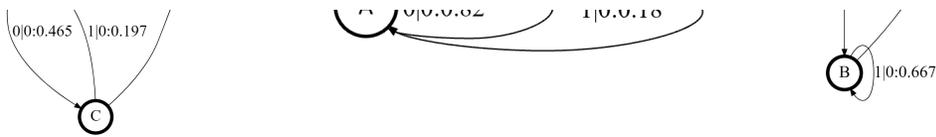


Figure 2: ϵ -machine representing users own behavior predicted based on their past behavior

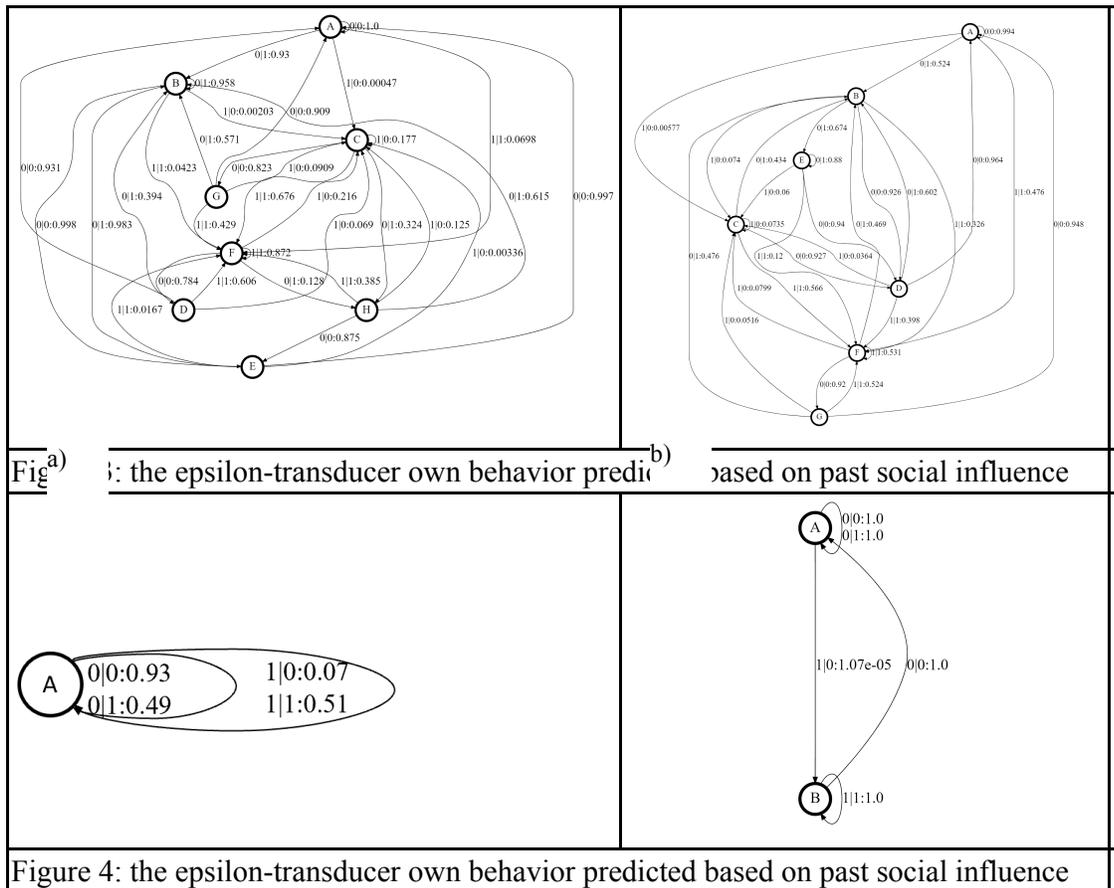


Figure 4: the epsilon-transducer own behavior predicted based on past social influence

Conclusion

Going back to the first research question posed earlier 2-states ϵ -machines suggest that there are hidden predictive states indicating hidden patterns, however, these patterns are not complex. For one user we saw 1-state ϵ -machine indicating no hidden patterns. Looking at the social influence models (ϵ -transducers), we observed much more complex hidden patterns for two users, however, for the rest of the three users the behaviors are rather simplistic. For RQ2, we observed complex hidden behavioral patterns influenced by users own past behavior and by social influence. In conclusion, we can say that both self and social influence can predict the future behaviors i.e., that negative sentiment expressions can be self-motivated as well as socially motivated. Users' negative sentiments can be influenced by the sentiments expressed in the parent comments i.e., negative sentiment contagion.

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