Modelling Emotion Dynamics on Twitter via Hidden Markov Model

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ABSTRACT

Exploring the mechanism about users' emotion dynamics towards social events and further predicting their future emotions have attracted great attention to the researchers. One of the unexplored components of human communication found online in written form is an emotional expression. However, despite the concreteness of the online expressions in written form, it remains unpredictable which kinds of emotions will be expressed in individual messages of Twitter users. To investigate this, we perform an investigation on observing emotions unfolding in a consecutive sequence of tweets for a particular user based on his/her past history. In this paper, we propose a method on given a set of tweets related with some events (identified by the usage of a hashtag), determines how those sentiments will be distributed on behalf of a person within a conversation. We present the Hidden Markov Model (HMM) to understand the nature of emotion dynamics in Twitter messages.

CCS CONCEPTS

• **Information systems** → **Sentiment analysis**; *Emotion dynamics*; • **Computing methodologies** → Model verification and validation;.

KEYWORDS

TESC, HMM, E-HMM, Baum-Welch algorithm, Emotion dynamics

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1 INTRODUCTION

Twitter Sentiment Analysis (TSA) is a currently hot research topic that embraces a large variety of tasks such as sentiment analysis or opinion mining [15], opinion formation [8], emotion measure [4], emoji prediction[21] etc. The last few years have evidenced a massive growth of sentiment propagation on Twitter. This propagation of sentiment into networks has spread on many different areas from professional to everyday life like viral marketing [19], political campaigns [20] and social advertising [13] and so on. A study [22] observe that social activities and interactions greatly effect people's day-to-day activities, lifestyle, reading habit etc. Moreover, the accessibility to the information provided by social media brings up a whole new class of sentiment analysis tasks related to the changing nature of sentiments along time. People's opinion towards public events or products may change over time, rather than staying on the same state. Even tracking users' dynamics opinion [3] helps a company to monitor critical feedback of the product and further adjust its marketing plans. A government can also utilize users' feedback about the new policy and forecast upcoming development [23]. Therefore, understanding the essential mechanism of emotion dynamics are of great importance.

In general, tracking emotion over time in Twitter have been used to predict events by finding a correlation between the sentiments and the events. Many researchers mainly concentrated on measuring the emotional state of the tweet. Some existing works only focus on opinion dynamics [3, 12] in the social network. Social dynamics not even restricted only on twitter conversation, an important study perform by Del Vicario et al. [7], where they proposed a new technique which combines automatic topic extraction and sentiment analysis of Brexit debate discussion on Facebook public pages. Some interesting studies have been conducted by both modelling and forecasting opinion dynamics behaviours over time in social network [3, 5]. Motivated by above observations on the effectiveness of using social network in different context, this paper proposed a mathematical model to understand the user's emotion dynamics mechanism on various social issues on Twitter. More specifically, our aim is to systematically attempt to answer the following research questions:

- Given a set of tweets related to some events, how do we optimize the model parameters for learning?
- How can we infer how emotion will be distributed from the observed sentiment-labeled tweets?

- How can we evaluate a user's emotional state on different events or topics?

To investigate the above questions, we collected our dataset from Twitter using *Search-API*[1] related to four different events. Emotional states of the users reflected in the post are determined for each tweet using Russell's model of affect which correctly classifies the emotions expressed in over 90% of text messages [9]. For each user against a topic/event, *Temporal Emotional State Chain* (TESC) is prepared. Details of the data preparation is given in Section 2. Next, we adopted Hidden Markov Model [16] over the collection of TESCs across different users and propose different initialization methods. We called them Emotion-based Hidden Markov Model (E-HMMs). This proposed E-HMMs method analyzes the impact of different initialization across different users against different events. Finally, Baum-Welch forward-backward algorithm [1] applied in order to learn the HMMs and evaluation is performed using the maximum-likelihood estimation (MLE). The performance of our proposed method is compared with different linear models such as DeGroot model [6], Flocking model [10] and Voter model [11]. The result shows that the adapted HMM has the highest accuracy among others.

2 DATA PREPARATION AND SENTIMENT MODELING

This section describes our experimental data preparation method and sentiment labeling technique against a topic or event. We focus on discussing different data collection methods and building Temporal Emotional State Chain by estimation of incoming/outgoing messages.

Table 1: Size of the datasets

Event/Topic	Categories	# of Tweets	# of Users	Avg # of Sent Tweets
#BlackMoneyDebate	Policy	616343	1260	4
#Brexit	Policy	686434	2688	6
#GrenfellTower	Accident	136821	2297	3
#SyriaGasAttack	Terrorism	10823	557	3

2.1 Data Collection and Pre-processing

For our purpose of analyzing real-time events, we chronologically retrieved tweets through the Twitter *Search-API* and created our own datasets as shown in Table1. The collected tweets mainly contain the following information (i) user information i.e., the user who posted the tweet (ii) tweet text (iii) type of tweet i.e., direct tweet, retweet, reply, quoted tweet (iv) time of posting the tweet. To study emotion evaluation, one should post at least two tweets. We therefore first identify users who have posted at least two tweets from the dataset.

For each participating user, we extract and arrange the tweets posted by the user in the order of posting time. As mentioned above, we assign an emotional state to each of the selected tweets to enable us to investigate the user's emotion dynamics while participating in social discussions. The details of the data preparation are discussed below.

[1]http://twitter4j.org

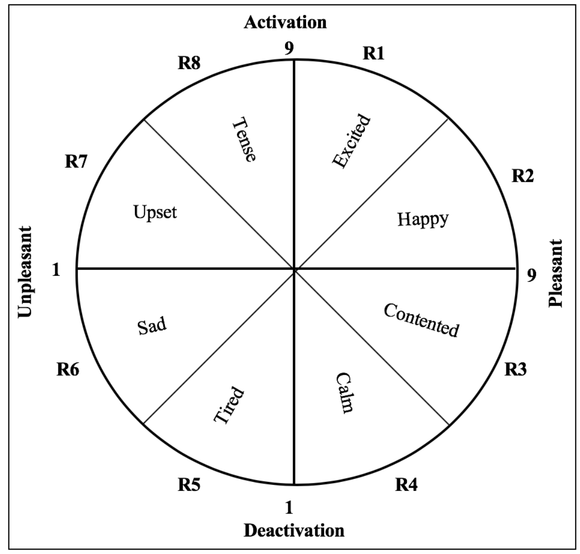

Figure 1: Russell's model : A circumplex model of affect with eight sentiments

2.1.1 Russell's Model of Affect. In the Russell's circumflex model of affect [17], emotions are understood as a combination of varying degrees of two main dimensions, *valence* (pleasure dimension) and *arousal* (activation dimension), which are distributed in a 2D circular space [18]. According to the Russell's model, every affective experience is the consequence of a linear combination of valence and arousal dimensions (the so-called core affect space), which is then interpreted as representing a particular emotion. A numerical value for valence ranges from 1 (*displeasure*) to 9 (*pleasure*) and arousal values range from 1 (*deactivation*) to 9 (*activation*). The core affect map identifies eight regions ($\mathcal{R}_u(i) \in \{1, 2, 3, \ldots, 8\}$) and named them as *Excited* (R1), *Happy* (R2), *Contented* (R3), *Calm* (R4), *Tired* (R5), *Sad* (R6), *Upset* (R7) and *Tense* (R8) [18], as shown in Figure 1.

2.1.2 Emotional State Labeling. To determine the emotional state of a tweet using Russell's circumflex model, we first need to estimate valence and arousal score of the tweet. To estimate valence and arousal score of a tweet, we use ANEW dictionary of affect [2]. It provides mean and standard deviation scores of valence and arousal for unique words in English. For example, the word *love* has mean and standard deviation value for valence as ($v = [\mu : 8.72, \sigma : 0.7]$) and that of arousal ($a = [\mu : 6.44, \sigma : 3.35]$). We then use the mean points to determine the emotional state in Russell's circumflex model, i.e., the coordinate (8.72, 6.44) falls in the *Happy* region (*R*2). In a given tweet, more than one emotional word may be present. Like in [14], we use the formula defined in the equation 1 to determine the overall emotional state of a tweet.

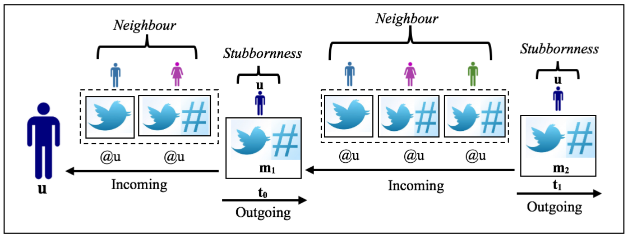

Figure 2: Temporal Emotional State Chain

$$X = \frac{\sum_{i=1}^{N} \frac{\mu_i}{\sigma_i}}{\sum_{i=1}^{N} \frac{1}{\sigma_i}} \qquad (X, \mu, \sigma) \qquad (1)$$

where,
X mean value of valence (similarly, mean value of arousal)
N total number of emotional words within the message
μ word's mean value of valence (equivalently for arousal)
σ word's standard deviation of valence (equivalently for arousal)

2.2 Temporal Emotional State Chain

This section describes the formation of a Temporal Emotional State Chain (TESC). Every participating user's data is defined by the sequence of *outgoing* and *incoming* tweets arranged in the order of posting time. Outgoing tweets are those tweets posted by the target user about the topic under consideration. Whereas the incoming tweets are those tweets posted by neighbours about target topic, and are received by the user, and are received by the user through one of the following: *Incoming hashtag* (InH), *Incoming mention* (InM), *Incoming reply* (InR), *Incoming retweet* (InRT).

Given a user u and a topic #h, a typical *temporal tweet chain* is defined by the following tuple chain, where $\downarrow$ denotes incoming and $\uparrow$ denotes the outgoing tweets.

$$< u, \#h > \longrightarrow \quad < .., \downarrow m^c_{t_{0-1}} >, \uparrow \mathbf{m_{t_0}}, <\downarrow m^c_{t_{0+1}}, .. >, \uparrow \mathbf{m_{t_1}}, <\downarrow m^c_{t_{1+1}}, \ldots >, \uparrow \mathbf{m_{t_2}}, \ldots$$

When the user u posts his first tweet at t_0 on topic #h, public discussion on the topic #h might have already taken place. It is denoted by the tuple $\downarrow m^c_{t_{0-i}}$, $i = 1, 2, ..$ and $c \in \{inH, inRT, inR, inM\}$. Similarly, incoming tweets between the user's tweet $\uparrow m_{t_k}$ and $\uparrow m_{t_{k+1}}$, is denoted by the tuple $<\downarrow m^c_{t_{k+0}}, \downarrow m^c_{t_{k+1}}, .. >$. An example is also shown in Fig 2.

The emotional state of a tweet in a *temporal tweet chain* is determined using Russell's circumflex model of affect as described in Section 2.1.2. If $\mathcal{R}_i, i \in 1, 2, 3, \ldots, 8$ denotes one of the eight emotional states for a given tweet, the above *temporal tweet chain* can be transformed into the following *temporal emotional state chain*.

$$< u, \#h > \longrightarrow \quad < .., \downarrow R^{InM}_{i, t_{0-1}} >, \uparrow \mathbf{R_{i, t_0}}, <\downarrow R^{InR}_{i, t_{0+1}}, .. > \uparrow \mathbf{R_{i, t_1}}, <\downarrow R^{InRT}_{i, t_{1+1}}, .. >, \uparrow \mathbf{R_{i, t_2}}, ..$$

In all the experimental analysis reported in the subsequent section, we use the above temporal emotional state chain for each user.

3 HMM-BASED APPROACH

This section describes one of the most paramount stochastic model and our proposed approach based on this HMM architecture. The Hidden Markov model (HMM) is a stochastic process that is an extension of Markov chains [16]. In HMM, the state is not directly visible rather output result is visible which depends on the finite state stochastic sequence. An HMM is denoted by the model $\lambda = (A, B, \pi)$. where,
A = State transition probability distribution
B = Observation symbol probability distribution
π = Initial state distribution

To create the HMM, the probabilities of the transitions among the hidden states and the emissions of the observable symbol must be calculated. If we would assume that the sentiment state of a user at time t is perfectly reflected by the sentiment of the tweet sent at t, then states would be directly observable. However, it seems reasonable to assume that the sentimental state of a user is also influenced by the tweet messages (s)he has received (incoming tweets). Although we have no means to know whether or not the user has read all the received messages mentioned by the u inside the body of text, we will assume so. Our method establishes that the sentimental state of a user who sends a message i at time t is a combination of R_i and the sentiments of the received messages from t_{0-1}.

Given a collection of tweets, we extract the sequence of tweets sent by each user $u_i \in U$ in the collection. Thus, for each user u we have a sequence of observations $O_u = \langle \uparrow m_{t_1} \ldots, \uparrow m_{t_k} \rangle$ that represent the sentiments of the k tweets sent by user u at a time t. More specifically, after labeling tweets with their corresponding Russell's region we will have $O_u = \{R_i\}^k_{i=1}$, where each message i is sent at a time t that we prepare in section 2.2. Sentimental states of users are likewise labeled with Russell's regions $R_1, R_2, \ldots, R_8$. Therefore, the HMM is defined with 8 hidden states $S_i = \langle s^1_i, s^2_i, \ldots, s^8_i \rangle$ and corresponding observations $O_k = \langle o^1_k, o^2_k, \ldots, o^8_k \rangle$. Let $\langle \uparrow R_{i,t_1} \ldots, \uparrow R_{i,t_k} \rangle$ be the sentiment of the tweet sent by the user at t and let $\langle \downarrow R_{i,t_{0-1}} \ldots, \downarrow R_{i,t_k} \rangle$ be the average sentiment of the messages received from $t - 1$ to t. The initial sentimental state of a user is calculated as a weighted average w of the sentiments of the send (w_s) and the received (w_r) messages. The initialization of the sentimental state corresponding to the emission is computed as the Russell's region within which the pair valence-arousal $\langle w_r \times \downarrow R_{i,t_{0-1}} + w_s \times \uparrow R_{i,t_1}, \ldots, w_r \times \downarrow R_{i,t_k} + w_s \times \uparrow R_{i,t_k} \rangle$ falls. We are aimed to testing whether a higher weight to the sentiment of the sent tweet reports a more accurate HMM. Therefore, we design different E-HMMs: E-HMM$_1$ with $w_r = 0.75$ and $w_s = 0.25$; E-HMM$_2$ with $w_r = 0.5$ and $w_s = 0.5$; and E-HMM$_3$ with $w_r = 0.25$ and $w_s = 0.75$.

To learn E-HMM and re-estimate the parameters of this model, we applied the most commonly used algorithm for HMMs, a form of Expectation-Maximization called the Baum-Welch algorithm [1]. E-HMM is trained with the 80% of the sequences O_i and S_i of the users, using the Baum-Welch algorithm until it converges. Once the E-HMM is fitted, it is tested with the remaining 20% of the samples. The best model estimator is computed as $\hat{\lambda} = argmax_\lambda L(\lambda)$ where $L(\lambda)$ is the log-likelihood of λ given by $L(\lambda) = \sum^m_{j=1} P(O_j|\lambda)$ for the observation sequences O_j of the m users. The best model is the one with the highest log-likelihood value.

4 EXPERIMENTAL EVALUATION

4.1 Dataset

For the purpose of our study, we collected our datasets with the *Search-API* related to four different events through the hashtags #BlackMoneyDebate, #Brexit, #GrenfellTower and #SyriaGasAttack respectively. It consists of 6.80K users over a total of 14.50M tweets. From the raw datasets, we filtered out users who sent 0 or only one message and tweets that did not show any emotion (null values of valence and arousal). Table 1 shown the final figures after filtering.

4.2 Model Estimation and Performance Analysis

Our application of the HMM enables us to understand the nature of changing emotions expressed in Twitter messages from the selected model. In this section, we represent the log-likelihood values for the final estimated models of the testing samples and the performance of our proposed methods. For validation of our methods, we compare it with the three baseline methods, i.e. DeGroot model [6], Flocking model [10] and Voter model [11].

4.3 Estimated Model Selection

Table 2 shows the log-likelihood values for the model obtained after the Baum-Welch process as a final model and in both cases (training and testing) can be seen a higher value. The models are then applied to the testing sets and the obtained results are coherent with the training dataset. It can be seen that E-HMM$_3$ yields to the best model for *BlackMoneyDebate*, *GrenfellTower* and *SyriaGasAttack* dataset. The initialization using a weight of 0.25 for the sum of all the read messages and an 0.75 for the written tweet consider to the best model. Whereas, E-HMM$_2$ is the best model for *Brexit* dataset where received and sent messages reflected the same weight(0.5). It seems reasonable that if an individual changes his/her sentiment into their conversation, stubbornness plays a major role than neighbour's opinion. It confirms that our proposed initialization methods result in better models with compare to other baseline methods. However, it can be observed that the final model obtained by E-HMM$_1$ hardly represents an improvement against other initial models. Therefore, we can conclude that E-HMM$_2$ and E-HMM$_3$ are better estimator of the training set for each dataset and the values obtained by E-HMM$_3$ support our hypothesis.

4.4 Evaluation Metrics on Emotions Prediction

The emotion prediction performance for all methods are evaluated after optimizing from the best model $P(O_j|\lambda_{best})$ to the sequence of O_j observation of the users. To evaluate the performance of our proposed method on a different topic, we have used two different measures of error. One is MSE (Mean Square Error):

$$MSE = \frac{\sum_{t=1}^{n} (A_t - P_t)^2}{n} \tag{2}$$

Another one is MAPE (Mean Absolute Percentage Error):

$$MAPE = \frac{\sum_{t=1}^{n} |\frac{A_t - P_t}{A_t}|}{n} \times 100 \tag{3}$$

where for both measures, A_t is the actual value, P_t is the predicted value and n is the number of user on each observation sequence.

Table 3 represents a comparative analysis of the prediction error (MSE and MAPE) of three state-of-the-art algorithms along with three additional variations of our algorithms. We observe that for all the datasets, the overall performance of our proposal is substantially better than all the baselines. Among the baselines, we found that E-HMM$_3$ performs best. If we look in an individual topic, E-HMM$_2$ method for *#Brexit* perform well with minimum error (i.e. 0.0044 MSE and 3.31% of MAPE). However, the variants of E-HMM$_3$ show a significant performance w.r.t. E-HMM$_1$ and E-HMM$_2$ which confirms our hypothesis. We compare our proposed methods with baselines in terms of prediction.

- The prediction performance of DeGroot is consistently good in comparison to other baselines. But during the training phase, this model was iterated multiple times to converge and predict the emotion.
- Flocking is comparatively better than the voter model and this model updates the emotion of a user by calculating the average value of his/her neighbours. If any user does not have any neighbours, then this model makes difficult to predict the right emotion of that user. Therefore, the performance of predicting polarity comparatively is completely poor.
- The performance of voter model is not much impressive than others. Since this model update user's emotion randomly, thus it cannot judge the actual emotional sequence for prediction. Thus, the performance of this model is unsatisfactory.

Finally, we can conclude that E-HMM$_3$ outperforms the other baselines and proposed methods in term of predicting emotion dynamics evaluation of the users. Apart from this, we can also apply E-HMM$_2$ method when the average sequence of user's post is much higher over the conversation.

5 CONCLUSIONS

In this paper, we have presented the Hidden Markov Model to express the nature of changing emotions from single-hashtag Twitter conversations. One of the most common Baum-Welch algorithms is applied for examining basic techniques for parameter estimation in HMMs. We propose a Temporal Emotional State chain framework to incorporate with the sentiment of the user's sequential tweets for sentiment prediction in emotion dynamics. Our main result contrast to the MLE approach to identify the best model by comparing with different initialization method. From our experiment, we examine several interesting observation. First, we found a proportion of linear combination of reading and written tweets are more feasible than other baseline methods. The initialization method highlights that the sentiments of the read messages have a different effect as the sentiment reflected in the message sent by the user within a conversation. In future, we would like to extend our

Table 2: Log-likelihood $P(O|\lambda)$ of three different initialization methods (E-HMM$_1$, E-HMM$_2$ and E-HMM$_3$) and other methods to be compared using DeGroot, Flocking and Voter.

Type	Dataset (#h)	DeGroot	Flocking	Voter	E-HMM$_1$	E-HMM$_2$	E-HMM$_3$
Train	#BlackMoneyDebate	-18,670.148	-19,309.548	-18,678.148	-18,668.148	-18,658.148	**-18,566.640**
	#Brexit	-13,395.508	-13,405.508	-13,541.474	-13,264.889	**-13,260.869**	-13,261.889
	#GrenfellTower	-8,336.055	-8,336.955	-8,337.585	-8,328.584	-8,327.908	**-8,326.584**
	#SyriaGasAttack	-2,022.426	-2,022.560	-2,022.740	-2,021.449	-2,009.907	**-2,009.889**
Test	#BlackMoneyDebate	-2,626.237	-2,637.909	-2,632.229	-2,624.042	-2,621.909	**-2,583.730**
	#Brexit	-4,014.747	-4,021.945	-4,076.250	-4,010.759	**-4,003.586**	-4,009.538
	#GrenfellTower	-2,096.062	-2,097.418	-2,097.516	-2,095.278	-2,093.376	**-2,091.455**
	#SyriaGasAttack	-540.712	-541.902	-543.870	-538.852	-537.992	**-537.883**

Table 3: Performance metrics of emotions prediction for each dataset. The first each column of the each dataset is forecasting error in terms of MSE and second one is MAPE with percentage.

Topic	#BlackMoneyDebate		#Brexit		#GrenfellTower		#SyriaGasAttack	
	MSE	MAPE(%)	MSE	MAPE(%)	MSE	MAPE(%)	MSE	MAPE(%)
DeGroot	4.5108	8.56%	6.8365	3.80%	0.1761	0.20%	0.0620	1.69%
Flocking	6.1113	8.68%	7.8695	4.06%	0.0160	0.94%	0.0854	1.76%
Voter	5.4055	8.58%	7.9333	4.07%	0.7439	1.76%	0.0882	2.09%
E-HMM$_1$	3.7958	8.25%	5.2553	3.75%	0.0008	0.09%	0.0169	1.00%
E-HMM$_2$	2.9189	8.07%	**0.0044**	**3.31%**	0.0021	0.08%	0.0163	0.99%
E-HMM$_3$	**2.0714**	**7.24%**	5.2553	3.75%	**0.0006**	**0.01%**	**0.0111**	**0.62%**

analysis with a large volume of a dataset by using deep learning architecture to find more accurate results.

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