Post-dased dredddtdon od dsersddddnions Employing the Social Impact Model Improved by Emotion

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Abstract— **Opinion formation is a collective behavior, describing the dynamics of people's opinions due to their interactions. Nowadays, social media are broadly used and cause a lot of interactions among users who mainly know each other merely as a username, but significantly influence each others' opinions and emotions. Both emotions and opinions spread across users in social media via their exchanged posts. Furthermore, based on psychology research, emotion affects people's opinion. In this research, we implemented two binary classifiers to predict the users' next opinions considering previous posts sent in online community: an original classifier, a classifier based on the social impact model of opinion formation; and an emotion-integrated classifier, a classifier based on the social impact model of opinion formation integrated with an emotion model to achieve an improved model. To evaluate the improved classifier, we used a dataset containing some debates from the CreateDebate.com website and compared the performance of the original classifier with the performance of the emotion integrated classifier. The experiment results show that considering emotions improves the accuracy and precision of the social impact model of opinion formation in social media.**

Keywords— Computational Social Science, Social Networks; Opinion Formation; Social Impact Model; Emotion.

1. INTRODUCTION

Online social networks are now used as a very popular media and a growing platform for users' connections. The users interacting in an online social network are generally anonymous and have low influence on each other, but according to the Granovetter's theory of weak ties [1], the large number of interactions, each of them with a little strength, could make a significant strength affecting on the users. Thus, online social networks are now very influential to circulate ideas and information and affect social decisions and social movements even in national and international scales.

For a government, company, or non-governmental organization, success and failure much depend upon the satisfaction of the related people and their opinion about the received services. Therefore, understanding the current opinions of related people about some specific topics, and more importantly understanding the trend of their opinion, is very critical. This trend of opinion could not be exactly determined, as Isaac Newton (1720) said: "I can calculate the motion of heavenly bodies, but not the madness of people." But having an estimation of opinion trend is possible and have been an interesting subject, entitled opinion dynamics and opinion formation models, for many researchers in the last few decades. An estimation of people's opinion helps governments and companies to revise their goals, missions, and strategies to achieve more successes and avoid dangerous pitfalls.

The traditional studies in social science were mainly based on limited data, collected with difficulties and in many cases encountered some challenges in the results such as bias. Nowadays, thanks to the online social networks providing a powerful platform for rapid interaction between people, even in different continents, a massive volume of data is available to study the social phenomena such as opinion formation in a computational social science approach [2].

The early opinion formation models were mainly focused on usual interaction among individuals, e.g., face-to-face interactions. Nowadays, due to the broad usage of online social networks and online communities, opinion formation on these platforms is an interesting research topic.

Not only opinions but also emotions spread along online social networks via the posts users send. On the other hand, research in psychology reveals that emotion affects opinion. Thus, combining emotion with opinion formation model could help us to achieve a more accurate estimation of opinion trends in online social networks.

In this study, to achieve a more accurate opinion formation model for online social networks, we propose a model integrating the social impact model of opinion formation [3, 4] and a computational model for emotion to treat emotion contagion and emotion influence on opinion. To examine how considering emotions may improve an opinion formation model, two experiment sets have been conducted to compare the results: the original social impact model of opinion formation, and the integrated model. Both models have been treated as binary classifiers and their performance have been compared according to the classifiers literature. The classifiers' inputs to predict any opinion change/continuity in the discussions are the previous posts sent to the online community. We consider the models as post-based models, means that any post influences the users who read the post.

Thus, the context of this research is online social networks or online communities and we interpret every post as an influential factor. The main question of this research is whether we can achieve a more precise social impact model of opinion formation by improving the model using the effects of emotions carried by the exchanged posts.

The rest of this paper is organized as follows: Section 2 contains a brief background, covering computational social science, opinion formation, social impact model of opinion formation, emotion modeling, and sentiment analysis; Section 3 explains the research method; the experiment results are presented in Section 4; Section 5 is dedicated to the discussion; finally, Section 6 concludes the paper.

2. Background

This section presents the fundamental concepts of this research. As this study follows a computational social science approach, this concept is briefly described. Then the opinion formation models, the social impact model of opinion formation, the concept of emotions and emotion modeling, and emotion detection from a text are described, which are the main pillars of this research.

2-1. Computational Social Science

"Computational social science is the study of social phenomena using digitized information and computational and statistical methods"[5]. Collecting data about individuals, networks, and population at the same time for experiments in empirical studies of traditional social science has always been a challenge. Nowadays, online social networks provide us a lot of valuable data, including exchanged posts among the users, which could be collected and be used to provides an opportunity for researchers to address fundamental social questions by using this valuable observational data in computational social science approach [2]. The computational social science mergers techniques from machine learning and statistics with ideas from social sciences [6].

2-2. Opinion Formation

Opinion formation is a process treated as a collective phenomenon [4]. The opinion formation models mainly focus on describing how opinions of some interacting individuals change as a result of their interactions. Many researchers in social psychology, statistical physics, mathematics, and computer science have contributed to opinion formation during the last few decades. The growth of online social network more reveals the importance of opinion formation models. A deep understanding of the opinion dynamics and having a mature opinion formation model, we can predict the people's opinion and can be used in many applications in different areas, e.g., political, economic, cultural, and social sectors.

Different opinion formation models are based on various assumptions. The most critical aspects of opinion formation models are: discreteness/continuity of opinion values; the interaction network among involved individuals; the impression of any interaction on the opinions; the dimensions for opinion space which could be one or more; the interpretation of time as discrete or continuous; and time-stability or time-variability of assumptions and limitations of the model.

French, the psychologist, introduced a simple and intuitive model in 1956 [7]. DeGroot [8] developed a mathematical discrete time model. Abelson [9] proposed a model similar to the DeGroot model, but it is a continuous time model using differential equations instead of difference equations. The Friedkin-Johnson model [10] assumes that the interacting individuals adhere to their initial opinions to a specific degree g_i and by susceptibility of 1-g_i are socially influenced by the others. The Deffuant model [11] and the HK model [12] are two basic models that utilize the concept of bounded confidence, which means that only close enough individuals interchange their opinions [13].

2-3. Social Impact Model of Opinion Formation

In this research, we focus on the social impact model of opinion formation [3, 4], which is based on the social impact theory in psychology [14]. The model describes how the impact on individuals is exerted by the real, implied or imagined presence or actions of one or more people or even groups, and they in turn influence other individuals. The model is suitable for online communities or forums, in which any user can send a post to express an idea, and other users receive it and may be influenced.

In the social impact model of opinion formation, there are N individuals in the system. The opinion of any individual i (i=1, 2, . . . , N) is denoted by o_i, which is equal to either -1, or +1. Any individual is also characterized by its persuasiveness (p_i) and supportiveness (s_i), the capability to convince another individual to change or continue his/her current opinion respectively. In the simplest version, any individual i experiences total impact I_i from (1):

$$I_i = \sum_{j=1}^{N} \frac{p_j}{d_{ij}^{\alpha}}(1 - o_i o_j) - \sum_{j=1}^{N} \frac{s_j}{d_{ij}^{\alpha}}(1 + o_i o_j) \quad , \qquad (1)$$

where d_{ij} denotes the distance between two individuals i and j. The distance is interpreted as geographical or abstract distance. The α parameter determines how fast the impact decreases with the distance d_{ij}. In some simulations of the model α=2 [15], however, its value is not usually greater than 8 [4].

The two summations on the right-hand side of (1) compute the impact of interacting individuals to change and support the opinion of individual i, respectively. Since o_i=±1 and o_j=±1, for opposite individuals o_j, (1-o_io_j)=2 in the former summation and (1+o_io_j)=0 in the latter summation. Therefore, the former summation computes the pressure from opposite opinions to change the current opinion. Similarly, the latter summation computes the pressure to persist in the current opinion. Thus, if the pressure of the opposite individuals dominates the pressure of the agreeing individuals, *i* changes its opinion. However, a random parameter, h_i, is regarded for the non-deterministic behavior of *i* and influences from environments. Therefore, the dynamics of opinion change is written as (2), indicating the opinion of individual *i* at time step t+1 regarding h_i and the social impact I_i which has been experienced at time step *t*. The sign function in (2) maps negative values to -1 and positive values to +1.

$$o_i(t \quad 1) \qquad sign\; o_i(t) I_i(t) \quad h_i \qquad\qquad 2$$

2-4. Emotions and Emotion Modeling

Emotion is another cornerstone of this research. The models proposed for opinion formation are mostly mathematical and pay little attention to the psychological influences of emotions on individuals' opinions. According to the results of previous studies, very similar to emotions contagion in face-to-face interactions, emotions spread via textual contents in online social networks [16, 17]. Therefore, the integration of a model for the emotions embedded in the exchanged posts into an opinion formation model could result in an improved opinion formation model for online social networks. In [18], an agent-based simulation combining the Deffuant model [11] with an emotion model to shows the effects of emotions on opinion dynamics.

One of the most accepted definitions for emotion among the psychologists is "a complex state of feeling that results in physical and psychological changes which influence thought and behavior" [19]. Some studies expose emotion contagion via social media. In [17], the essential role of emotion contagion via social media in some social movements is discovered. A study on millions of Facebook users shows emotion contagion from citizens in a rainy city to their friends in other cities who are not experiencing rainfall [16].

Emotions are mainly modeled adopting one of these two approaches: modular or discrete; and dimensional. The modular approaches use terms such as anger, fear, disgust and so forth to specify separate modules, whereas in dimensional approaches the emotions are differentiated via a two or more dimensional space [20]. Every point in the multidimensional model of emotions implies a specific emotion. Almost every module in the modular approach could be mapped to a point in the space of a dimensional approach. The multidimensional emotion modeling approach is an appropriate approach for computational treating with the emotions.

In computational emotion modeling, emotion is usually described in a two or more dimensional space. The valence, which measures the pleasure related to the emotions, is often one of the dimensions in dimensional emotion modeling and is the essential factor in emotional persuasiveness and supportiveness power.

2-5. Sentiment Analysis

Similar to the emotions embedded in face-to-face conversations, every post sent to online social networks and communities carries emotions. To detect emotions from text, known as sentiment analysis, three main approaches are used: lexicon-based, rule-based, and machine learning-based [21], and some combined approaches.

SentiStrength [22, 23], which is used in this research as a tool to detect the emotions of textual posts, has been successfully used in some other researches [24-28]. This tool uses a lexical approach and contains some rules to deal with standard linguistic and social web methods. The core of its algorithm is a sentiment word strength list, derived from 298 positive terms and 465 negative terms, classified for either positive or negative sentiment strength with a value from 2 to 5 based on human judgments. The most important rules are:

Idiom list: to detect the sentiment of a few common phrases.

Spelling correction: to delete repeated letters in the words (e.g., "hellp" to "help")

Boosting word lise: to strengthen or weaken the semtiment of next sentiment words (e.g., "very" and "somewhat").

Negation word: to neutralise the next sentiment word (e.g., "I do not hate him", is not negative).

Emotion list with polarities: to identify additional sentiment (e.g., ":)" scores +2)

Repeated letters or punctuation: to emphasis (e.g., "a loooong time", "Hi!!!")

Based on the presence of both positive and negative emotions [29], SentiStrength assigns one positive score from the interval [1,5] and similarly, one negative score from the interval [-5,-1].

3. RESEARCH METHOD

The research method is simply based on comparing the results of an empirical investigation of two models of opinion formation on a dataset collected from the CreateDebate.com online debate website [30]. Both models are treated as binary classifiers to predict the next opinions of the users regarding the previous posts in the discussion. The comparison of the output of the classifiers for the same input is mainly based on confusion matrix and receiver operating characteristic (ROC) curves [31], which is popular to evaluate classifiers in the machine learning literature.

3-1. Dataset Specification

We used a dataset containing 61 discussions and about 3000 posts about "gun control" from CreateDebate.com online debate website. Every discussion is started by a user with a title and possible stances, commonly yes/no, for/against, or agree/disagree stances. Any interested user reads previous posts and participates in the discussion choosing one of the possible stances and sends one or more posts to support the selected stance. Figure 1 shows a visual representation for a sample discussion, entitled "Should guns be banned in America?". In Figure 1, the horizontal axis indicates the temporal sequence of posts. In the original dataset, stances have been tagged with 0 and 1 value, while to be compatible with the social impact formulas we treated the stance 0 as the opinion -1. Every circle stands for a post, and a consecutive time step is assigned to every post. The two vertical areas (top and down) of the figure is dedicated to the two possible stances, e.g., zero and one. Every line stands for one user, which contains one or more circles (posts) sent from the user. Any user's opinions may be in just one stance or both stances. The red lines and circles stand for the posts starting with stance 0, and the green ones stand for the posts starting with stance 1. The information about this discussion mentioned in the figure shows that the discussion contains 72 posts sent by 14 users, the first stance for four users were 0 and for ten users were 1. At the end of this discussion, we have seven users with stance 0 and seven users with stance 1. In summary, six users have changed their stances 13 times in this discussion.

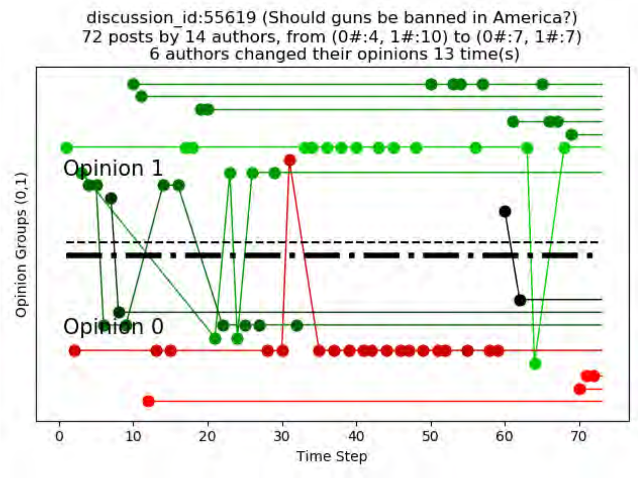

Fig. 1. A sample visual representation of discussion posts.

3-2. Dataset Pre-processing

For this research, we prepared the dataset in the following steps:

Data cleaning: At this step we removed the inconsistent data and those which are not useful for this research.

Valence computing: The valence value of every post computed and assigned using SentiStrength. The sentiment lexicon of SentiSrtength includes about 2500 words, while we extended this lexicon to about 14000 terms using the Warriner's sentiment lexicon [32].

Discussion statistics extraction: At this step, the required statistics from the discussions were extracted, including the number of posts, the number of users, and the mean value of posts' valences. Because we are interested in change and continuity of opinions, the first post of every user is considered as his/her first opinion and the second, third, etc. posts are considered for change or continuity of opinions.

Extracting a subset of the dataset: In order to have discussions with enough number of posts to analysis, the discussions with less than 50 posts were removed from the dataset at this step. After this data removal, the dataset was reduced to a subset including

- ○ Number of discussions: 17
- ○ Total posts: 2157
- ○ Total users (authors): 716
- ○ Number of posts in the biggest discussion: 642
- ○ Number of posts in the smallest discussion: 52
- ○ Number of posts continuing the previous stance of the post owner: 1197
- ○ Number of posts changing the previous stance of the post owner: 235

3-3. Analysis using Social Impact Classifiers

We implemented two binary classifiers to predict the next opinion of any user considering the previous posts exchanged in the online debate forum based on the original social impact model: an original classifier, and an emotion integrated classifier. The classifiers predict the change/continuity of the users' opinions, which is one of the two possible stances specified in any discussion. Since the classifiers predict change/continuity of opinions, they are meaningless for the first post form a user because there is no previous stance to be compared; therefore, the classifiers have not been applied on the first post from each user in the discussions.

The classifiers apply the social impact model and relevant formulas (1) and (2) on the refined dataset, considering every previous post has an influence to change/continuity of the opinion stance of the user under study. The analysis approach is mainly based on comparing the experiment results from applying these two models to the dataset.

The following parameter assignments are the same when applying (1) and (2) in all the experiments in this research:

p_j and s_j: for these two parameters for persuasiveness and supportiveness power of any individual, constant value 1 was assigned similarly.

: the constant value 2 was assigned to this parameter.

Another key parameter is the distance between any two individuals i and j, d_{ij}. We considered two interpretations for this parameter:

The distance between any two individuals equals 1.

The previous posts are partitioned into two groups. One group contains *k* posts at the beginning of the discussion and *k* posts immediately before the current time step. When a user reads a discussion post, the early and late posts in the discussion are more influential posts. Thus we assume a close distance equal to 1 for these posts and a far distance equal to 2 for the other posts in the middle of the discussion. We also assumed k=15 because the average number of posts to be shown in a web page of the CreateDebate.com is about 15 posts.

The distance of an individual from himself/herself, self-supportiveness, could be considered in several ways, thus produces various versions of the social impact model of opinion formation. We supposed that the individuals are just impacted by the people to whom they interact, in other words, the individuals are completely open-minded and do not persist on their previous opinion. In some studies, a specific function has been defined for self-supportiveness [4, 33].

To compute the emotional impact of every previously sent post *j*, we computed a valence factor for the post, vf_j, using (3):

$$vf_j \quad sign(v_j) \quad v_j / 2, \qquad (3)$$

where v_j is the valence value of post *j*. Using this equation, vf_j takes a value between -3 to +3. Now, we rewrite (1) as (4) to consider emotions.

$$I_i \;\sigma\upsilon \sum_{j\gamma 1}^{N} \frac{p_j}{d_{ij}}(1,\; o_i o_j)vf_j \;\alpha\sigma\sigma \;\nu \int_{j\gamma 1}^{N} \frac{s_j}{d_{ij}}(1\,\omega o_i o_j)vf_j \;\eta\sigma \qquad (4)$$

As summarized in Table 1, the experiments were conducted in four configurations regarding the combination of valence considering and two types of post distance measurement.

4. EXPERIMENT RESULTS

The output of each experiment is a confusion matrix, showing the number of true and false predicts for the change/continuity of opinions, and a receiver operating characteristic (ROC) curve. To be compatible with the terminology of confusion matrix measures, we regard opinion change as the "positive" class and opinion continuity as the "negative" class. Table 2 shows the confusion matrix for the experiment I2_v as a sample, including true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

The following statistical measures briefly describe the performance of a classifier:

Accuracy: (TP+TN)/(P+N)

Precision: TP/(TP+FP)

Recall or Sensitivity: TP/P

Table 3 shows the confusion matrix measures on the selected subset of the dataset, sorted on accuracy measure.

Figure 2 shows the mean of the absolute valence of posts in the discussions of the dataset and Figure 3 shows a more detailed view of the accuracy measures of the discussions corresponding to the discussions shown in Figure 2. Considering these two figures the trend of the accuracy values regarding the discussion emotion is observable. Similarly, Figure 4 shows the values of precision measures on the discussions. In this figure, the precision for a random classifier which classifies the classes randomly is also shown. Indeed, the imbalance of the number of class members (change/ continuity) causes this low value of precisions. The average precision measure of a random classifier on the dataset is calculated as (5):

$$Pr = TP/(P+N) = 235/\,(235+1197) = 0.16. \qquad (5)$$

Table 3 shows the values of precision measures for every experiment as a measure on all of the samples. Although the precision values are relatively low, some improvements have occurred in the experiments on the improved models.

TABLE 1. EXPERIMENTS ON DATASET

Experiment name	Distance	Considering Valence
I1	1 for all posts	No
I1_v	1 for all posts	Yes
I2	1 for close posts, and 2 for far posts	No
I2_v	1 for close posts, and 2 for far posts	Yes

TABLE 2. CONFUSION MATRIX FOR I2_V EXPERIMENT

		Predict		
		Opinion change	*Opinion continuity*	*Total*
True	*Opinion change*	TP=117	FN=118	**P=235**
True	*Opinion continuity*	FP=490	TN=707	**N=1197**
	Total	**607**	**825**	**1432**

TABLE 3. CONFUSION MATRIX MEASURES

Experiment name	Accuracy	Opinion Change		Opinion Continuity	
		Precision[a]	Recall	Precision	Recall
I2_v	0.59	0.20	0.51	0.86	0.60
I1_v	0.59	0.20	0.49	0.86	0.61
I2	0.41	0.14	0.51	0.80	0.39
I1	0.39	0.14	0.50	0.79	0.37

a. Expected precision for a random classifier: 0.16

Figure 5 shows ROC curves for the experiments I1 and I1_v. The ROC curve is created by plotting the true positive rate against the false positive rate at different thresholds.

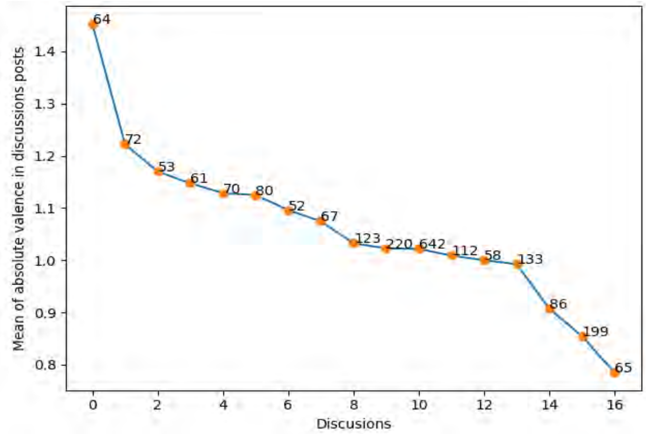

Fig. 2. Mean of absolute valence for posts in the investigated discussions.

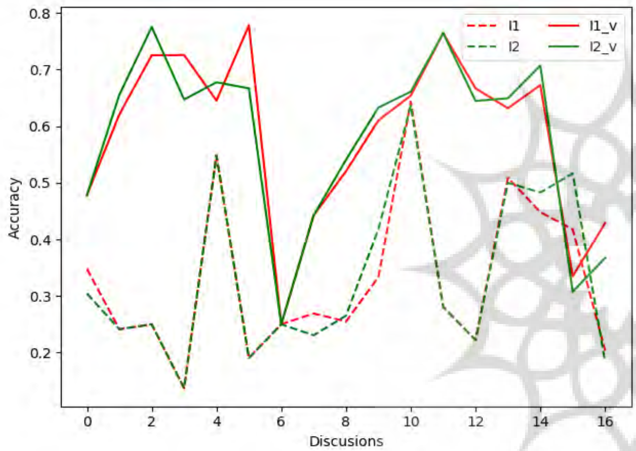

Fig. 3. The accuracy parameter in correspondence with discussion shown in Fig. 2.

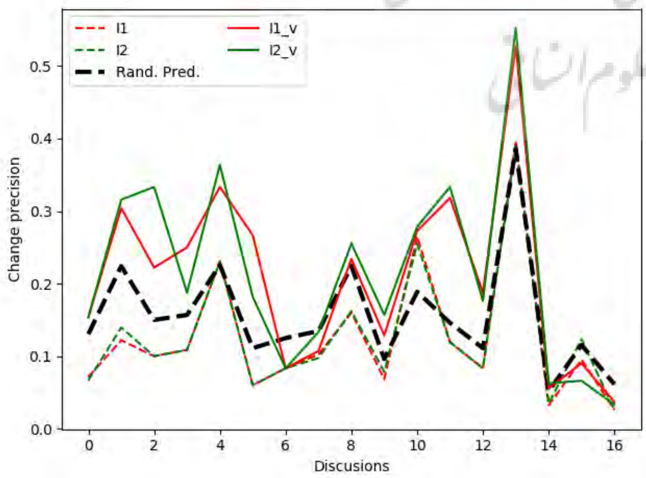

Fig. 4. The precision parameter for prediction of change opinion in correspondence with the discussions shown in Fig. 2.

The point for threshold=0 is also shown on the curves, corresponding to the threshold in the social impact model of opinion formation. The sign function in (2) determines change or continuity of individuals' opinions based on the sign of its argument; therefore, the threshold is zero to change/continue the opinion stance. The area under curve (AUC) in a ROC curve determines the performance of the classifier. For a perfect classifier, AUC=1, and for a random classifier shown in diagonal thin dashed line in the figure, AUC=0.5. As the figure shows, AUC increased from 0.43 for the original classifier to 0.56 for the emotion-integrated classifier.

Similarly, Figure 6 shows the ROC curves for I2 and I2_v experiments, and the improvement is obvious comparing AUC which increases from 0.44 for the original classifier to 0.57 for the emotion-integrated classifier.

5. Discussion

The primary goal of this research was to attempt to find a way to achieve a more accurate social impact model of

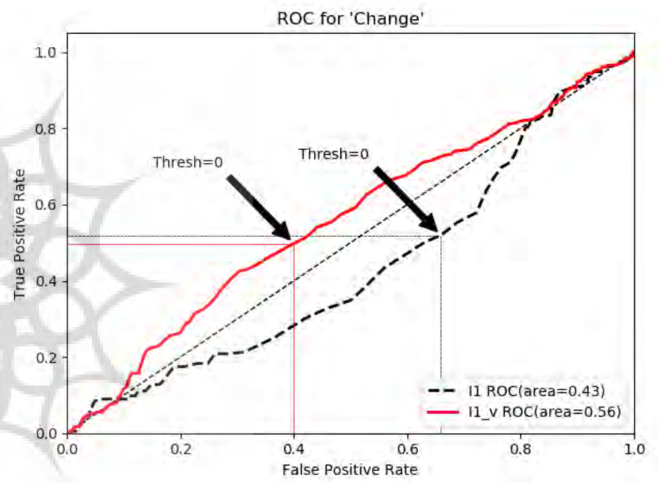

Fig. 5. ROC curves for I1 experiment, original classifier (dashed black), and I1_v experiment, emotion-integrated classifier (solid red)

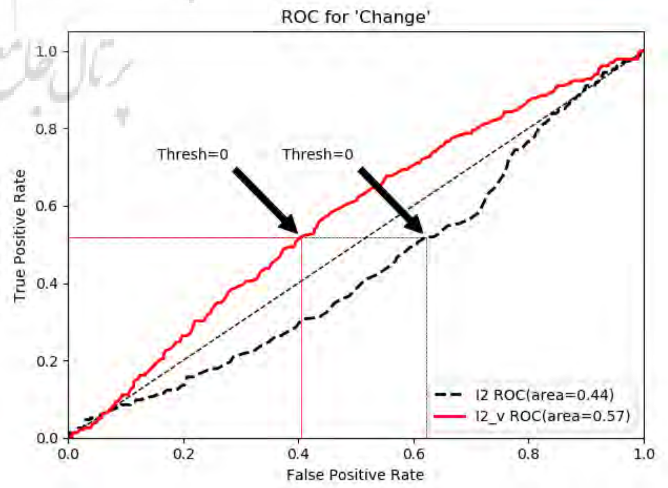

Fig. 6. ROC curves for I2 experiment, original classifier (dashed black), and I2_v experiment, emotion-integrated classifier (solid red)

opinion formation in online social networks by integrating the original model with an emotion model. The emotion model was considered to model both emotion contagion and effect of emotion on opinion.

The literature has not discussed the integration of opinion formation model with an emotion model. As expected, our experiments show that considering emotion to produce a more comprehensive opinion formation model, results in a more comprehensive and accurate model to describe opinion dynamics in online social networks. Our assumption could be inferred from experiment results shown in Table 3, Figure 3 and Figure 4. As this results show, confusion matrix measures for original models, I1, have been improved in I1_v, and similarly, measures for I2 have been improved in I2_v. The only reason for this improvement is integrating the opinion formation model with an emotion model because other parameters were the same.

Since the discussions are sorted on the mean of absolute valence for their posts (Figure 2), very interestingly, the diagrams of Figure 3 and Figure 4 show a correlation between emotions in the discussions and performance of the model. Although this correlation is not very rigid, the diagrams show more performance of the proposed model regarding the accuracy and precision of classification for discussions with higher emotion.

Contrary to expectations, we found that based on the classification measures, the performance of the original opinion formation model in most cases of our dataset is weaker than a random classifier. The reason for this rather contradictory result is still not entirely clear. Although we selected some reasonable assumptions for our experiments, these assumptions may be refined in the future researches. We feel strongly that we achieve an even more accurate model if the revised assumptions could generate a more accurate original model.

The context of the experiments is a key point in this research. We have chosen the subjects on "gun control," but there may be some other subjects that people are more or less rigid on their opinions. In other words, in some topics, people's opinions may change affected by others more easily or seldom, regardless of the emotions exchanged by the posts. Furthermore, since the emotions have different impressions on different people groups (e.g., the young or the old, the men or the women), the demographics of the discussion is also another context-related parameter. We had no demographical data in our dataset; therefore, no analysis from this viewpoint was possible.

6. Conclusion

In this study, an improvement in the social impact model of opinion formation was introduced. This improvement is based on considering the emotion carried by the exchanged posts among the users. Two characteristics of emotion have been used based on psychological studies: the emotions contagion, and the effect of emotions on individuals' opinions. To evaluate the proposed model, the original model and the improved emotion integrated model have been applied to a subset of discussions from the CreateDebate.com website containing users' posts. The people's stochastic social behavior, h_i parameter in the social impact model of opinion formation, is the main factor that causes the model to be a rough model. However, considering emotion could improve the model in many cases, especially when the posts contain more emotional loads on average.

The experiment results of this research lead us to conclude:

- Considering emotion in the social impact model of opinion formation in online social networks could increase the accuracy of the model to predict the change/ continuity of individuals' opinions.
- In the discussions with more emotional posts, more improvements to the social impact model are achieved by integrating the emotion in the model.

It is possible that a number of limitations might have influenced the results obtained:

- The original social impact model has an intrinsic non-deterministic part which causes the model to be a rough model.
- We assumed no self-supportiveness for the individuals. In other words, the individuals are open-mind and do not persist in their current opinions, but it is not entirely true according to psychological studies.
- Although SentiStrength is a powerful tool we used in this research, emotion detection from text is an open problem and more accurate tools may increase the performance of the proposed model.
- According to the method of this research, the opinions should be expressed explicitly as opinion stances from a set of limited choices. Therefore, the available datasets for conducting this research are limited.

Regarding the limitations, we propose further studies to achieve a more improved model in the following areas:

- Finding a method to more precisely estimate h_i, the non-deterministic part of the social impact model of opinion formation. Focusing on contemporary influential sources, e.g., public media about the topics and investigating users' demography could be helpful.
- Studying the self-supportiveness could help us to achieve a more accurate computational model and consequently a more improved model. However, a more detailed study concerning the context of modeling, including characteristics of the individuals is necessary to deal with self-supportiveness in the model more accurately.

δ Other opinion formation models than the social impact model could be studied in similar studies.

- Using more mature tools to detect emotion from text could improve the results of this research.

Achieving and using bigger datasets with various topics and various user demographics is useful to reach more comprehensive results.

Applying the progress in psychological aspects in the context of online social networks and communities related to emotion, opinions, effects of emotion on opinions, and emotions contagion could improve the results.

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