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Information Virality Prediction using Emotion Quotient of Tweets

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Abstract— Happiness travels quickly in comparison to sadness or disgust, but proliferation of anger and fear surpasses them all. This defines the bottom-line of information virality on social media. Pertinent psychological studies convey that human emotions may be ‘activated’ or ‘deactivated’ to drive people to take action. Based on this, we propose the use of cognitive behavioural features to assess the virality of information in tweets by finding a dominant emotion of same type across tweets as an indicator of viral spread. Fluctuations in emotions convey uncertainty and may reduce the frequency and intensity of discussion of a trending topic. The proposed virality prediction framework detects the emotion quotient (EQ), a measure of emotional intensity associated with five emotions, namely, fear, disgust, sadness, anger, and happiness for the exposed information in tweets to predict its outburst, i.e., virality, pertaining to social and political issues. The hybrid (lexicon + supervised learning) approach using parts-of-speech (adjectives, adverbs, verbs, emoticons) is proffered to transform the tweet into an emotional vector representative of the sentimental value for a trending topic. This emotional quantifier is then used as an empirical evidence to determine the likelihood of information going viral based on the strength of emotion in tweets and its no. of re-tweets. Preliminary results clearly demonstrate the effectiveness of the approach which affirms information virality.

Keywords— Viral, Twitter, Emotion.

I. INTRODUCTION

Social media has the power to make any information, be it true or false, go viral and reach and affect millions. Good, bad, true, false, useful, useless all kinds of information proliferates through the social web platforms. The widespread activation of information propagation across meta-networks is referred to as the “virality”. The magnitude of social media virality cannot be overrated. It can bring fame and prosperity but at the same time can beget notoriety and nuisance. Social networks have been witness to the self-reinforcing Echo Chambers which steers a confirmation bias (false sense of affirmation that we are right in our beliefs) and relevance paradox (readers only consume information that is relevant to them, kind of one-sided).Twitter is one of the most popular social networks worldwide and as per the statistics for the first quarter of 2018, this micro-blogging service averaged at 336 million monthly active users globally [1]. The platform is used as a communication channel by businesses, celebrities and even government. Encouraging vigorous participation in such channels can be intentional or unintentional with the activities ranging from supporting a cause, getting involved, expressing personal feelings or beliefs, attention seeking, self-ambitions, finger-pointing someone, viral marketing, prank or to spread fear & hatred. Information virality refers to the inevitable cascading effect of information spread online which eventually proliferates across meta-networks and affects millions. In October 2017, the *#MeToo* movement created a wave of global reckoning for being posted by women who say they’ve faced sexual harassment and assault [2]. The impact of these two words was so much that it soared across social media including, Facebook and Instagram. It was one seismic activity which demonstrated the fortitude of social platforms and its virality.

Figure 1. Social Media Virality and its effect

Thus, it becomes exceedingly imperative to resolve the accuracy of information and promptly inhibit it from spreading among the Internet users as this can jeopardize the well-being of the citizens. Pertinent psychological studies convey that humans are intrinsically not very good at differentiating conflicting information. Naive Realism and Confirmation Bias further add to the vulnerability. Though the cascading model of tweet-re-tweet captures the virality of a tweet over its lifetime, the likelihood of content going viral has more to do with how activated the person felt after reading it. Crucially, it's just not the volume of tweets that matter, but the "homogeneity" and "irregularities" in the emotion that can make the difference. Thus the hypothesis laid is that "As unverified information spreads considerably on social media, it works with the same mechanics as that of a large protest where an outsized share of same emotion is representative of the response sensitivity. That is, emotions may be 'activated' or 'deactivated' to drive people to take action and a dominant emotion of same type across tweets is indicative of a viral spread. Fluctuations in emotions convey uncertainty and may reduce the frequency and intensity of discussion of a trending topic." Based on this, we propose the use of cognitive behavioural features to assess the virality of information in tweets. The proposed technique detects the emotion quotient (EQ), a measure of emotional intensity associated with five emotions, namely, fear, disgust, sadness, anger, and happiness for the exposed information in tweets to predict its outburst, i.e., virality, pertaining to social and political issues.

The approach is to transform the tweet into an emotional vector representative of the sentimental value for a trending topic. A lexicon based technique is employed to associate the emotional values for the words in the sentence. Parts of speech like adjectives, adverbs and some groups of verbs and nouns have been reported as good indicators of fine-grain sentiment across pertinent literature [3, 4, 5]. In this research, the adjectives, the verbs and the adverbs are considered as the emotion carriers in the sentence for feature-level emotion analysis. In natural language, the adjectives help to express the fundamental feelings and emotions within a tweet. The verbs operate as polarity markers as they convey the tone associated with the emotion. Similarly, the adverbs act as emotion bolsters, which scale the emotion polarity in terms of strength. For example, the occurrence of adverb "not" in "not bad" inverts the emotion value of the next word whereas the occurrence of adverb "ruthlessly" amplifies the emotion value of the next word. The use of emoticons has become a mainstream culture in social content writing and their use cannot be ignored as they suggest adjectives which add tone and clarity to the communication. Basically, the emoticons influence emotional communication. Studies suggest that emoticons, when used in conjunction with a written message, can help to increase the "intensity" of its intended meaning. Thus, the emotion analysis tool works by assigning emotion value to each adjective and emoticon in the sentence and obtaining the polarity value of verbs and the strength of adverbs.

In order to set the benchmark for empirical analysis with the created adjective emotion lexicon base, we apply classifiers. We analyze six supervised learning algorithms namely, Support Vector Machine (SVM), Decision Trees (DT), Logistic Regression (LR), Multi-layer Perceptron (MLP), Random Forest (RF), K-Nearest Neighbors (K-NN) for predicting the adjective emotion values for each tweet. The emotion quotient for each tweet is then calculated using a linear equation with scores from all four lexicon base. This patterning of emotions with time along with the number of times a tweet is re-tweeted measures the viral value of a tweet. Finally, the cumulative strength of viral values across all tweets is computed to detect a strong indicator of viral spread, i.e. virality of information. Once a tweet is identified as viral, tools and techniques that authenticate its source and veracity can be employed to mitigate any intentional and wrongful circulation. Further, this technique can be considered as a preliminary step to detect a possible rumour for which the actual truth value needs to be determined with accuracy & without delay.

The rest of the paper is organized as follows: Section 2 discusses the background work in this direction of virality prediction and specifically the use of emotions in viral posts on Twitter. Section 3 puts forward the details of the proposed framework, the Virality Prediction Framework followed by its implementation in section 4. Section 5 illustrates the results obtained and their analysis followed by the conclusion in section 6.

II. RELATED WORK

The term 'Virality' is originally from the biological sciences where the viruses contagiously spread among organisms. But recently, the term has found a new technological meaning with its social media presence. It is more than the basic person-to-person broadcasting and relies on word-of-mouth. "Going viral" and "Viral marketing" are two buzz terms reigning the online marketing and economics. Primary and secondary studies have been reporting the virality of content (tweets, posts, videos, photos) on social media.

Weng et al. [6] proposed a prediction model for information virality detection on Twitter using data about community structure. They show that, while most memes indeed spread like complex contagions, a few viral memes spread across many communities, like diseases. Using the proposed model the authors also demonstrate the future popularity of a meme by quantifying its early spreading pattern in terms of community concentration. Hoang et al. [7] present a virality model of twitter content to find viral tweets, viral users and viral topics. The highly viral messages, topics and users in GE2011 are extracted and evaluated using the model.

Berger and Milkman [8] were the pioneers to add psychological approach to online content virality. The authors suggest the relationship between emotion and transmission to understand what becomes viral. Hansen et al. [9], study the relation between affect and virality to understand the psychological and sentimental arousal theories. The dataset includes three corpora: tweets about the COP15 climate summit, random tweets, and text corpus including news. The findings also present evidence that negative sentiment enhances virality in the news.

The work presented in this paper is based on the hypothesis of Berger and Milkman [8] that “Virality isn’t born but made”. That is, it is made by the users, for the users and to the users and is motivated by why users’ converse and share information which is psychologically & emotionally triggered.

III. INFORMATION VIRALITY PREDICTION FRAMEWORK

The intent of the work proposed in this research is to create a framework that will enable predicting a viral tweet by virtue of its public emotion strength. The following figure 2 depicts the proposed framework.

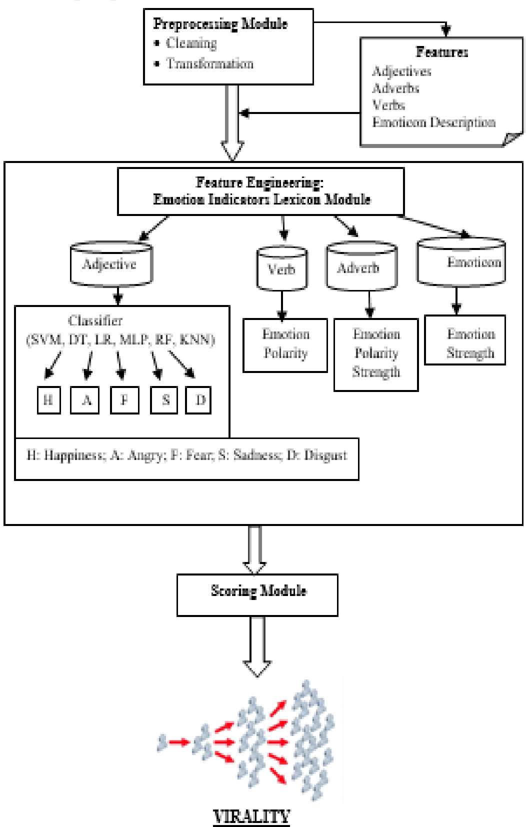

Figure 2. Information Virality Prediction Framework

As a typical text mining task, this framework consists of three modules, namely, the pre-processing module, the emotion indicator lexicon module and the virality scoring module.

It is important to make note that although the use of emoticons like Winking ;) and Sticking tongue out :P is widespread but it opens up a new avenue of research, as the use of these emoticons is related to a sarcastic, humourous, non-serious, joking tone of the post which may completely reverse the emotion conveyed by the textual indicators. For

A. Pre-processing Module

The tweets pertaining to a topic (#topic) are extracted from the publically available Twitter datasets using its API. In order to intelligently mine the text in tweets, pre-processing is done for cleaning and transforming the data for relevant feature extraction.

- Primarily the pre-processing includes cleaning the text by removal of redundant tweets, all URLs, hash tags, @username and non-English words followed by the transformation of text for relevant feature extraction. Sometimes people may use hashtags to convey direct and explicit emotions, for example #sad but we have omitted these as our main aim to predict the strength of emotion and not just the emotion.
- Text transformation firstly replaces the emoticons in text with their descriptive text or phrase. As the name suggests, emoticons are emotion icons and convey the emotions similar to human facial expressions. Their use has become a mainstream culture and so these cannot be omitted as they suggest adjectives which add tone and clarity to the communication. Emoticons influence emotional communication. Researchers found that emoticons, when used in conjunction with a written message, can help to increase the “intensity” of its intended meaning [10]. For example, the emoticon ☹ will be replaced by its description “*sad face*” and will be assigned an emotion strength value of -0.5. Thus we replace all the emoticons with their description and polarity using the values presented in the table 1 below. The list is an updated version of our earlier attempt [3] to decipher and use emoticons.

Table 1. Emoticons

Emoticon	Description	Emotion Strength
:-D	Big Grin	1
XD	Laughing	1
<3	Heart	1
:), =), :-)	Happy, Smile	0.5
:*	Kiss	0.5
0:)	Angelic	0.5
:|, :-|	Straight Face, Indifferent	0
:\	Undecided	0
:(, =(	Sad	-0.5
</3	Broken Heart	-0.5
=O, :-o	Shocked	-0.5
:’(	Cry	-1
X-(	Angry, Frown	-1
xP	Disgusted	-1

example, a tweet “We will all be killed then…Lets meet in heaven ;)” is a humourous tone whereas the textual emotion analytics will detect this as a negative one. For the framework defined in this paper, we have omitted the use of any such emoticons and have only considered the ones defined in table 1.

Next, using a POS tagger, only the adjectives, verbs and the adverbs are extracted to build the feature set. The emotion scores are then assigned to these to compute the final emotion quotient for the tweet.

B. Emotion Indicators Lexicon Module

The adjectives, verbs and adverbs are expressions of sentiments which convey emotions strongly. Adjective is that part-of-speech which describes, qualifies and identifies a noun or pronoun. Verbs express activity in terms of an action, an occurrence, or a state of being. Adverbs are words that change the meaning of a verb, adjective. In unison, these three parts-of-speech and emoticons quantify the emotion strength and will assist in capturing the growing emotional response of online users associated with a topic (an event, a person, a place, an issue). The lexicons for all these three emotion indicators are created and assigned values through a crowdsourcing initiative. Also, supervised learning models have been empiraclly analyzed for prediction of adjective emotion category. The details of each lexicon is explained.

A corpus of most commonly used adjectives created and validated in our earlier research [4] has been used for creating and assigning values to emotion tuples. The sample emotion tuple value for few adjectives is represented in table 2. The emotion values are assigned on a scale of 0 to 5 for five emotions in the vector, namely, fear, disgust, sadness, anger, happiness.

Table 2. Adjective Emotion Values

Adjective	Happiness	Anger	Sad	Fear	Disgust
damaging	1.33	3.5	3.06	2.73	2.42
dirty	1.28	2.3	1.94	1.94	3.7
easy	3.92	1.11	1.15	1.19	1.09
easygoing	3.98	1.14	1.14	1.14	1.11
ecstatic	4.08	1.34	1.31	1.8	1.52
elated	3.93	1.21	1.19	1.17	1.12
famous	3.32	1.3	1.21	1.2	1.38
fantastic	4.07	1.19	1.31	1.25	1.22
greedy	1.41	3.14	2.68	2.27	2.94
hard	1.65	2.22	1.75	2.21	1.4
innocent	3.17	1.37	1.49	1.66	1.27
lazy	1.49	2.01	1.83	1.4	2.39
menacing	1.17	2.94	1.78	1.97	2.18
merry	4.38	1.07	1.14	1.08	1.08
noisy	1.39	2.97	1.39	1.41	1.45
nonchalant	1.85	1.4	1.31	1.26	1.47
protected	4.11	1.24	1.33	1.47	1.08
proud	3.18	1.55	1.29	1.58	1.26
quartan	1.39	1.18	1.17	1.17	1.15
rejected	1.05	3.5	3.91	3.47	2
relaxed	4.32	1.12	1.14	1.1	1.04
scared	1.14	2.41	3.02	4.09	1.83
scornful	1.16	3.31	2.13	2.17	1.74
serious	1.45	1.92	1.84	1.97	1.29

Further, we analyze six supervised learning algorithms namely, Support Vector Machine, Decision Trees, Logistic Regression, Multi-layer Perceptron, Random Forest, K-Nearest Neighbors for predicting the adjective emotion values for each tweet. The details about these techniques are given in the table 3 below:

Table 3. Supervised Learning Techniques

Technique	Description
Logistic Regression (LR)	One of the most basic classification techniques, logistic regression utilizes a logistic function, also known as sigmoid function. It associates each input value with a coefficient (ϴ), and trains the given system to adapt to expected output value by modifying these ϴ values
K-Nearest Neighbours (K-NN)	K-NN is a classification algorithm that is based on feature similarity; that is, it focuses on similarities between values in a class. It treats input values as vectors in a feature space, and is based on votes given by its k nearest neighbors. K-NN is a lazy learning algorithm; it doesn’t generalize through available data, but instead represents the data as it is.
Support Vector Machines (SVM)	SVM represents the dataset as a map in such a way that there’s a clearly defined gap between the classes. Its approach depends on number of classes and the representation of its mapping.
Decision Tree (DT)	A DT symbolizes a set of rules, which help us to determine the class an input belongs to. The decision making process of these trees starts from the root, traverses downwards and ends up at leaves. The leaf nodes of a decision tree represent the values of an attribute. The other nodes are called decision nodes, which test given values and determine factors that help us classify them as we go downwards. Its training involves selecting the appropriate attribute to split the tree at each stage, while keeping the tree compact and organized.
Random Forests (RF)	RF Algorithm overcomes the limitations of DT method, by creating a forest of trees. The higher the number of trees, the greater is the accuracy of the system. It selects random subsets of the training input with replacement and fits decision trees in accordance with those samples, also called Bagging. This technique decreases the variance of the model, by averaging it out across many trees thereby cancelling noise and giving it the ability to generalize again.
Multi-layer Perceptron (MLP)	MLP is a type of feed-forward artificial neural network which uses back propagation as a supervised learning technique. MLP can adjust themselves to the data without any explicit specification of functional or distributional form for the underlying model.

Thus, the adjectives are analyzed and classified for five pre-defined emotion categories namely Happiness, Anger, Sadness, Fear and Disgust. The classification results are evaluated based on precision, recall, accuracy and F-score as the performance measures. We discuss the results in section 5.

Out of the five emotion categories considered for this work, happiness is the only emotion which has a positive polarity whereas the other four, namely, anger, sadness, fear and disgust have negative polarity. The natural language words conveying anger, sadness, fear and disgust are often related to anxiety and depression in humans. These are the “trigger” emotions which drive people to take action which makes it more likely to pass things as a chain reaction. Thus, to identify the category of emotions we determine the polarity (positive or negative) of the verbs. An emotion polarity lexicon base for 100 most commonly used verbs is created and the polarity values are assigned within the range of +1 to -1. Further the strength of this polarity is assessed using an adverb emotion polarity strength lexicon base created for this research. The respective emotion polarities & strengths within both the lexicon-base have been congregated through a crowd-sourcing task. The polarity strength value and emotion polarity for few adverbs and verbs is shown in table 4 and table 5 respectively.

Table 4. Adverb Emotion Polarity Strength

Adverb	**Emotion Polarity Strength**
Extremely	+1
Terribly	0.9
Seriously	0.8
Totally	0.7
Completely	0.6
Most	0.5
Too	0.4
Very	0.4
Highly	0.4
Pretty	0.3
More	0.2
Much	0.1
Any	-0.1
Quite	-0.2
Just	-0.3
Little	-0.4
Dimly	-0.5
Less	-0.6
Not	-0.8
Never	-0.9
Hardly	-1

Table 5. Verb Emotion Polarity

Verb	**Emotion Polarity**
Love	1
Adore	0.9
Won	0.9
Like	0.8
Enjoy	0.7
Kiss	0.7
Smile	0.6
Impress	0.5
Attract	0.4
Excite	0.3
Relax	0.2
Kill	-1
Shoot	-1
Revenge	-1
Hate	-1
Destruct	-0.9
Harm	-0.9
Hurt	-0.8
Fight	-0.8
Beat	-0.7
Hit	-0.7
Yell	-0.6
Lost	-0.5
End	-0.4
Detest	-0.2
Reject	-0.1

The seed lists of positive and negative adverbs and verbs whose orientation we know is created and then grown using the WordNet [11]. That is, for each Adverb and Verb occurring in a tweet, it is checked for its presence in the seed list. If it is a hit, the values are assigned and returned else in case of a miss, WordNet is used to extract synonym and antonym with known value and assigned the value accordingly.

C. Scoring Module

Once the emotion value from all indicators is extracted, the next step is to gauge the emotion quotient of the tweet for subsequently calculating the viral value of a tweet and virality of a topic.

$$EQ = \frac{1}{a+b+c+d}\left(\frac{\sum_{i=1}^{n}|E_{adj}|_i}{n*5} + \frac{\sum_{i=1}^{m}|E_{vb_i}|}{m} + \frac{\sum_{i=1}^{p}|E_{avb_i}|}{p} + \frac{\sum_{i=1}^{q}|E_{emot_i}|}{q}\right) \quad (1)$$

where, ${E_{adj}}_i$, ${E_{vb}}_i$, ${E_{avb}}_i$, ${E_{emot}}_i$ are the emotion values of adjective, verb, adverb and emoticon respectively. As these quantify the strength of the emotion, we take the mod of values;

n, m, p and q are the number of adjectives, verbs, adverbs and emoticons present in the tweet;

The parameters a, b, c and d are used to signify the presence of the emotion indicators. For example, if an adjective is absent, the value of will be 0 and if it's present the value of a will be 1. This has been done to dampen the values of emotion quotient such that they are normalized within the range of 0 to 1. The value of the parameters is assessed as shown in table 6 below:

Table 6: Parameter Values

Parameter	Value =0	Value=1
a	n=0	n>0
b	m=0	m>0
c	p=0	p>0
d	q=0	q>0

Next, based on the emotion quotient of a tweet, the viral value of the tweet (VV_{tweet}) is calculated using the following equation (2)

$$VV_{tweet} = Polarity\left[\frac{EQ*R}{T}\right] \qquad (2)$$

Where, the Polarity is in terms of positive or negative sentiment (indicated by + or -). It determines the emotional factor of the post. Out of the five emotions considered, fear, anger, sadness and disgust are negative emotions whereas happiness is a positive one. But in the absence of an adjective in tweet, this polarity classification is not possible. So, we propose that, as the adverbs qualify adjectives and verbs, the adjective group (adjective*adverb) or the verb group (verb*adverb) polarities will determine the overall polarity of a particular tweet. This is imperative in determining the emotional orientation of the posts as the strength of same emotion type will be a yardstick of virality.

EQ is the emotional quotient of the tweet calculated using equation 1;

R is the no. of re-tweets, that is, the total no. of times the tweet has been reposted;

T is the time, that is, the life span of the tweet counted in number of days.

In most of the models, the volume of re-tweets is the key indicator of virality but this will yield any topic with more re-tweets to have a high viral value even if it is a post from the past. The rationale is that a tweet with more than 5000 re-tweets in a single day has more viral value than the same 5000 re-tweets in 7 days. Moreover, social media platforms like YouTube define viral videos as videos with more than 5 million views in a span of 1 week but no such virality benchmarking has been done for twitter posts. So the main aim is to detect the virality of a post in the present so that steps to mitigate the risk of wrongful information from being spread can be taken promptly.

A transaction file is maintained for each tweet on the topic storing the emotion quotient, its polarity, no. of re-tweets, life-span and the viral value of the tweet. Thus the virality score for information, V_{info}, is the cumulative emotion quotient calculated using the following formulae in equation (3)

$$\text{V (info)} = \sum_{i=1}^{t} EQ_i \quad for\ i, \ldots\ldots, t\ tweets \in \#topic \quad (3)$$

As discussed earlier, out of the five emotions considered, fear, anger, sadness and disgust are negative emotions whereas happiness is a positive one. A cumulative negative viral score is indicative of a similar sense of outrage among the members of the virtual community. Thus, the strength of same emotion across posts is the yardstick of virality. That is, the information further needs to be checked for veracity and origin to restrict flare-up of rumour.

The implementation details and a sample calculation are illustrated in the next section.

IV. ILLUSTRATION

Basically, the work carried out encompasses the following:

- Feature Engineering
- Implementation of six supervised learning techniques to empirically analyze a better classifier for adjective emotion value detection
- Quantifying the emotional value of tweet and cumulative emotional value across tweets for a topic.
- Virality Scoring

To clearly illustrate the effectiveness of the proposed method, a case study is presented with a sample set of tweets.

Sample Tweet: Let us consider a sample tweet on trending topic #Texasshootout which has 870 re-tweets in 1 day and compute its emotion quotient (EQ), Polarity and Viral Value (VV_{tweet})

> After the brutal shootout in school, children harmed…bombs to kill more! I am scared :'(#Texasshootout #lifeunderthreat

A. Pre-processing of Tweets

After downloading tweets using the #topic, the data is cleaned by removing hashtags, usernames, hyperlinks, RT symbol, punctuations and non-English characters. The emoticons are transformed to the description as defined in table 1. Stemming and tokenization is also performed for pre-processing the tweets. Stemming is done on text in order to preserve the root of the word, for example it reduces harming to its root word i.e. harm.

> After the brutal shoot in school children harm bomb to kill more I am scare *cry*

B. POS Tagging

Subsequent to the pre-processing, only the adjectives, adverbs and verbs are extracted from the feature set. Each tweet is parsed using CMU Twitter POS tagger. The resultant file is a list of tweets that only have adjectives, verbs and adverbs (in the original order), which are referred to as emotion indicators.

brutal	shoot	harm	kill	more
ADJECTIVE	**VERB**	**VERB**	**VERB**	**ADVERB**
scare	*cry*			
ADJECTIVE	**EMOTICON**			

C. Emotion Scoring

Once the POS tagging is done, the words are scored using the crowd-sourced lexicon values. The above parsed tweet is thus scored as follows:

- Here we can see that "brutal" & "scare" are adjectives, "shoot", "kill", "harm" are verbs, "more" is an adverb and "cry" is the description of emoticon.
- The adjective emotion values of "brutal" and "scare" are represented by the vectors [1.16, 3.65, 2.99, 3.28, 2.86] and [1.14, 3.31, 2.13, 4.09, 1.83] respectively such that the values in vector are representative of [<Happiness>, <Anger>, <Sadness>, <Fear>, <Disgust>] as shown in table 2
- Classifier detects the emotion polarity of adjectives as Anger for "brutal" and Fear for "scare", which are both negative emotions, giving a polarity of -1 to the tweet
- The emotion polarity for the verbs, "shoot", "kill" and "harm" are assigned as -1, -1. -0.9 respectively
- In the list of adverbs we get the emotion polarity strength values of "more" as 0.2 (from the table 5)
- The polarity value of cry from emoticon table 1 is -1
- Now using equation (1), the EQ of the tweet will be computed as follows:

$$EQ = \frac{1}{1+1+1+1}\left\{\left[\left|\frac{E_{brutal}+E_{scare}}{2*5}\right|\right] + \left[\left|\frac{E_{shoot}+E_{kill}+E_{harm}}{3}\right|\right] + \left[\left|\frac{E_{more}}{1}\right|\right] + \left[\left|\frac{E_{cry}}{1}\right|\right]\right\}$$

$$= \frac{1}{4}\left\{\left|\frac{3.65+4.09}{10}\right| + \left[\left|\frac{(-1)+(-1)+(-0.9)}{3}\right|\right] + \left[\left|\frac{0.2}{1}\right|\right] + \left[\left|\frac{-1}{1}\right|\right]\right\}$$

$$= \frac{1}{4}\left\{[0.774] + \left[\frac{0.9667}{3}\right] + [0.2] + [1]\right\} = 0.25\{[0.774] + [0.322] + [0.2] + [1]\}$$

$$= 0.25 \times 2.296 = 0.574$$

Thus, the EQ of the Tweet is 0.574 and the polarity from classifier is negative, -1.

- Now using equation (2), the VV_{tweet} is computed as follows

$$VV_{tweet} = (-1)\left[\frac{0.574 * 870}{1}\right] = -499.38$$

- Similarly we calculate the values for the other tweets on the same topic as shown in the following table 7:

Table 7. Illustration of Scoring Module

Original Tweet	Features	Emotion $Quotient_{Tweet}$	Polarity	Re-tweet	Life-span	Viral $Value_{Tweet}$	Virality (Info)
This is pretty serious…We will all be killed </3 :'(#texasshootout #scared	Pretty(Adv) serious (Adj) all (Adv) kill (Vb) *broken heart cry (Emoti)*	0.6485	-1	1105	1	-716.59	

More kills! They are terrorist! School children hurt X-(=O #texasshootout #godhelp	More (Adv) kill (Vb) hurt (Vb) *angry shocked (Emoti)*	0.6166	-1	700	1	-431.62	+186.90-5713.52 = -**5526.62**
Innocent people & children killed. Are they humans? Terrible it is Xp X-(:-o #texasshootout #rip #inhuman	Innocent (Adj) kill (Vb) hate (Vb) terrible (Adv) *disgusted angry shocked (Emoti)*	0.842	-1	1402	1	-1180.48	
Bravo! Great work… the school for rich people! :-D :P #texasshootout #wedeserveit	Great (Adj) work (Vb) rich (Adj) *big grin(Emoti)*	0.756	+1	247	1	+186.90	
Bombs to kill planted! Highways closed as extreme violence reported. Scared to death ;(=O #texasshootout #disturbed	kill (Vb) plant (Vb) close (Vb) extreme (Adv) scare(Adj) *cry shocked (Emoti)*	0.767	-1	3762	1	-2885.45	

- Using equation (3), the virality of the topic is -5526.62 and it is observed that the dominant emotions are similar in tone for a viral topic. Based on further experimentation, the threshold for a topic being called "viral" has been set to 5000. So any value of virality greater than 5000 implies that the topic has a cascading effect and steps to authenticate its accuracy and origin must be taken by agencies (business or government).

- The + and – simply indicate the polarity of the post.

Thus, using the proposed virality framework the likelihood of content going viral can be determined and this can be an initial step to identify and highlight information with questionable veracity. The next section discusses the results obtained .

V. Results and Discussion

This section highlights the results and observations related to performance of the proposed framework. The empirical analysis results demonstrate that the virality model effectively finds the viral information. The preliminary results are clearly motivating.

The findings were further analyzed for the adjective emotion classifier performance using the measures: Accuracy (A), Precision (P), Recall (R) and F-score for the various supervised learning techniques [12, 13]. The following table 8 describes the results of the adjective emotion classifier**:**

Table 8. Performance Results

Measures → / **Techniques**	**A**	**P**	**R**	**F**
K-NN	70.6	0.71	0.71	0.71
SVM	85.6	0.85	0.86	0.86
DT	84.8	0.85	0.85	0.85
RF	89.1	0.89	0.89	0.89
MLP (NN)	91.2	0.90	0.92	0.91
LR	92.0	0.91	0.92	0.92

It is observed that Logistic Regression and Neural Networks give the highest accuracy scores (92% and 91% respectively). As the data was crisp and concise, high values for all four metrics were observed. Next to it are RF and SVM depicting 89% and 86% accuracy. DT came next with a comparable accuracy of 85%. K-NN showed the lowest accuracy of around 71%. It is interesting to note that using Ensemble methods such as Random Forests gave improved and enhanced results in comparison to the traditional single Decision Trees model.

The following Figures 3, 4, 5 and 6 depict the results shown in table with the help of graphs.

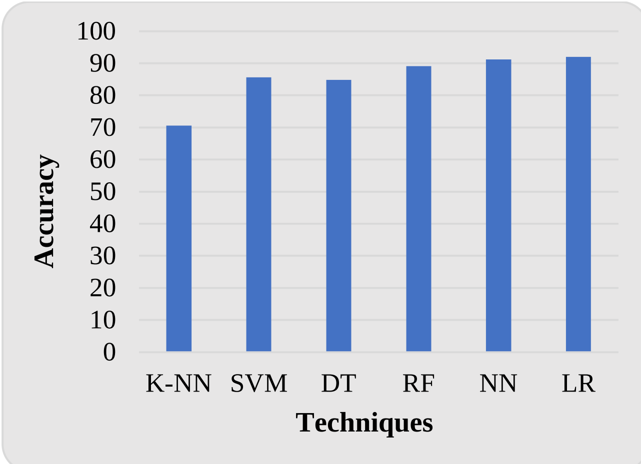

Figure 3. Accuracy

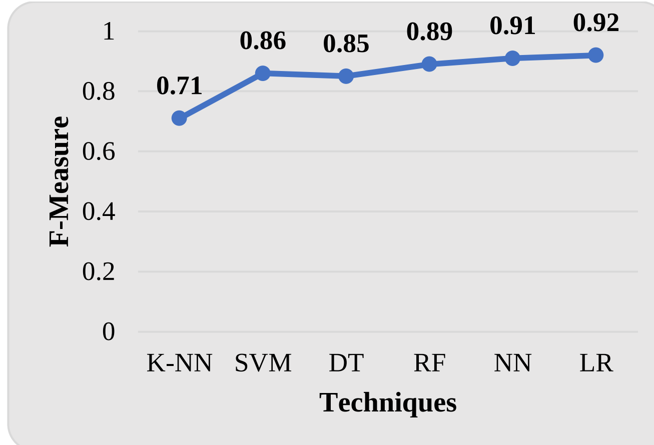

Figure 6. F-Measure

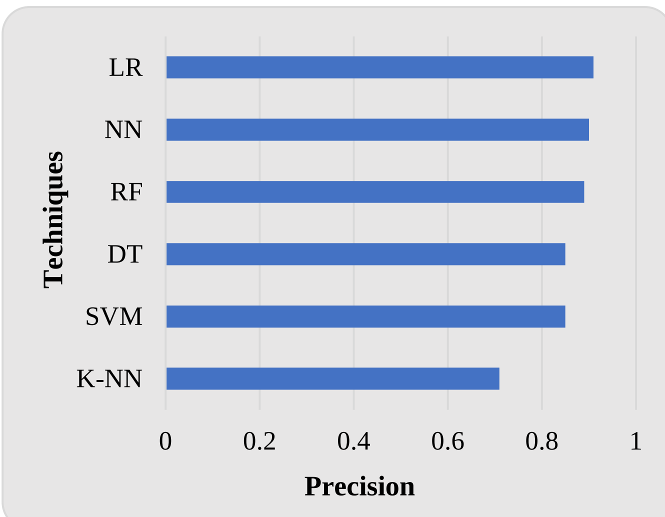

Figure 4. Precision

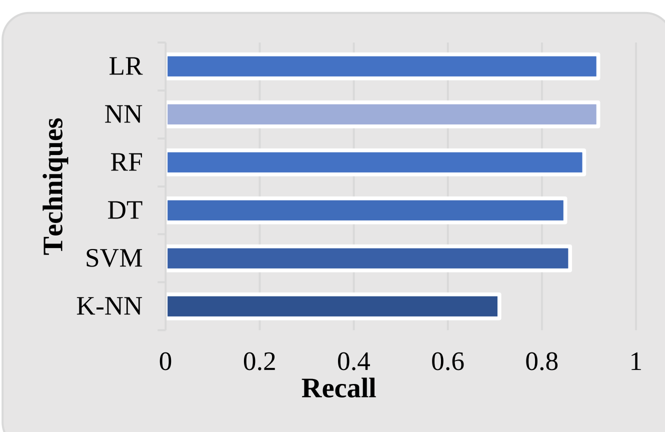

Figure 5. Recall

Finally, the for the following socio-political topics: #texasshootout; #MeToo; #TakeAKnee; #Covfefe; #YemenInquiryNow; #308Removed; #plastickills; #KarnatakaElections2018; the framework is able to determine the virality value of the topical information along with its sentiment polarity and fine-grain emotion value.

VI. CONCLUSION AND FUTURE SCOPE

Sharing online content is an indispensable part of our contemporary lives. Consequently, it becomes exceedingly imperative to resolve the authenticity of information and promptly inhibit them from spreading among the Internet users as it can jeopardize the well-being of the citizens. The proposed virality framework determines the likelihood of content going viral based on the strength of similar emotion across the tweets on a topic. The hybrid approach makes use of natural language textual cues of emotions from parts-of-speech like adjectives, verbs, adverbs and emoticons. The empirical evaluation of supervised learning techniques used for emotion classification of adjectives yields the best results for logistic regression followed by the neural network (multi-layer perceptron). The virality of social and political topics is perceived accurately using the scoring module. As a future direction of work, the fluctuations in emotions can be captured as they convey uncertainty towards a topic and may assist in veracity check or rumour stance detection. The framework can be used to draw a correlation of virality to rumour in order to acquire a list of potential rumours, for which the truth value needs to be determined. Also, contextual information within the post can be assessed for virality prediction.

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