A Proposed Model for Detecting Facebook News' Credibility

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***Abstract*—Social networks are currently one of the main News' sources for most of their users. Moreover, News channels also consider social networks as main channels not only for spreading the news but also for measuring the feedback from their followers. Facebook Followers can comment or react to the news, which represents the follower's feedback about this topic. Therefore, it is a fact that measuring the News' credibility is one of the important tasks that could control the propagation of the fake news as well as the number of News' followers. The proposed model in this research highlights the impact of the News' followers on detecting the News' polarity either it is fake or not. The proposed model focuses on applying an intelligent sentiment analysis using Vector Space Model (VSM) which is one of the most successful techniques on the users' comments and reactions through the emoji. Then the degree of credibility is determined according to the correlation coefficient. An experimental study was applied using Facebook News dataset, which included the News and the followers' feedbacks.**

Keywords—Social network; vector space model; correlation coefficient; sentiment analysis

I. Introduction

Earning experiences from colleagues and friends has been considered long time ago [1] [2] [3] by different methods, however, a focus on social media source is recently highlighted. Considering applying mining techniques in different fields to support text analysis as well as emotion analysis has been proposed by different research such as in [4] [5] [6] and in [7]. The popularity of Social Networks are continuously increasing not only from population but it is also considered as a main resource to formal News' institutes. This population has led to a continuous focus from a large number of researchers [8], [9] [10]. Specifically, Facebook has a leading position among other social networks [11]. One of the main popular features in Facebook is the ability to express and share a reaction by different methods either by text, image, emoji, and others as well as the ability to control the privileges of others on this reaction. However, users may share fake news with no intention as they have no way to measure its credibility while they may become one of the main resources of credibility detection [12] [13]. Therefore, many research have been proposed for detecting the posts' polarity [9] as well as the fake news [14] [15].

Focusing on Facebook, different situations may be highlighted, the users' contribution may be not relevant to the post or a spam [13] [16]. Therefore, focusing on different users' response such as comments and emotions is considered one of the success factors for measuring credibility [17] [18]. The proposed model in this research considers detecting the credibility according to the comments and emotions analysis.

The remaining of this paper is organized as follows. Section 2 provides the technical background that is used in the rest of the paper. Section 3 defines our proposed model and the modifications that had been done on the original one. Section 4 studies our methods in a case study. Finally, Section 5 contains the conclusion and future work.

II. Background

There are several definitions and techniques used in the proposed model. Each one used for a specific purpose identified in section IV. These definitions and techniques are:

- Facebook reactions and their polarity [17] [8] [9].
- Vector space model: for measuring the text similarity between the post and comments on this post [19] [20].
- Sentiment analysis: for measuring the polarity of the comments on the tested post [21].
- Correlation coefficient: for measuring the convergence between the result from Facebook emotions and the analysis of post [21] [22].

A. Facebook Reactions

Facebook released the ability to respond by emotions in February 2016 additionally to the like emotion. Currently, six emotions are available to express the users' reaction represented in figure 1, they are as follows [23]:

a) Like: represents liking of the proposed post or comment.

b) Love: represents more than liking and express more empathy about the post.

c) Wow: represents surprising feeling that the post expresses unexpected act or event.

d) Haha: represents a funny reaction like irony or laugh.

e) Sad: represents sadness about specific action or event, also it reflects the refusal of the post.

f) Angry: represents the disliking of the post or comment.

Figure 1 demonstrates the well-known Facebook reactions:

Fig. 1. Facebook Reactions [24].

These emotions have different polarity [25] [14] [26], they are either positive (+1), negative (-1), or idle (0), and these emotions are classified according to their polarity. The following is a classification for the emotions:

a) Like: the default response which indicates that the post is seen, (0 polarity).

b) Love: a positive response which indicates that the reader admire the post contents, (+1 polarity).

c) Wow: a positive response which expresses the reader finds the post interesting, (+1 polarity).

d) Haha: a positive response which expresses that the reader finds the post funny, (+1 polarity).

e) Sad: a positive response which represents the reader sadness for the post contents, (-1 polarity).

f) Angry: a positive response which expresses the negative effect on the reader from the post contents, (-1 polarity).

B. *Vector Space Model*

Different algorithms have been proposed [27] [28] [29], however, Vector space model (VSM) is one of the most popular and successful. VSM contributes to an algebraic model that is able to provide a vector representation to the text document. VSM is popularly applied for index terms extraction, documents indexing, and documents ranking [19]. Measuring text documents similarity is applied using similarity measures such as cosine similarity [30] [31] , Euclidian distance [32].

C. *Sentiment Analysis*

Sentiment Analysis refers to the process of analyzing a document [21] which focus on a determined topic such as a situation or a product and classify the type of document according to the owner's attitude, either he likes or dislikes this document content with respect to the strength level of this attitude.

Text emotion classification methods have been demonstrated in different research with a filtration approach such as in data [33] [34]. Sentiment analysis could be performed using different approaches such as Sentiment Identification Algorithm which is Compositional Semantic Rule, Numeric Sentiment Identification, Vector space model, and Bag-of-Word and Rule-based. All these algorithms are used in Machine Learning Model which involves several classifiers such as Decision Tree, Random Forest, Logistic Correlation and Neural Network. [25].

D. *Correlation Analysis*

Correlation approach measures the degree that two variables are supporting each other [35]. The correlation coefficient measures how much a variable has an impact in changing the other variable performance and is able to change its value.

- A correlation coefficient is +1 when the increase of the variable leads to a fixed proportion increase positively to the dependent variable.
- A correlation coefficient is -1 when the increase of the variable leads to a to a fixed proportion decrease to the dependent variable.
- A correlation coefficient is 0 indicates that the two variables have no relation and there is no impact of one to the other.

III. Proposed Model

The proposed model follows the previously discussed techniques for measuring the post credibility [36] [37], this section demonstrates how these techniques are correlated and reformed in a homogenous model to support the required target. The proposed model is divided into three main phases as follows:

A. *Preprocessing Comment Text*

The text preprocessing is processed through several steps: [26] [20] [38].

Step 1: Spelling check

One of the main steps is performing a spelling check as preliminary step to avoid errors in the following phases. This step requires a dictionary that contains expressions in different forms like verbs, adjectives, nouns, etc.

Step 2: Text Preprocessing

This step aims to perform a tokenization process or text normalization. It includes eliminating white space and punctuations, Stemming, stop word removal and case folding by transforming the capital letter to lower case.

Step 3: Part of Speech Tagging

Part-of-Speech Tagging targets to read the text in a specific language and assign a tag to each token to define its type such as nouns, verbs, adjectives, etc.

Step 4: Building Vector

In this step, the extracted tokens are stored as a vector. This step is preparatory step for applying the vector space model for measuring the sentiment analysis in the next process. As Vector space model depends mainly on the idea of similarity, therefore, cosine similarity measure [8] was selected as it proved to be efficient in the field of sentiment analysis.

B. Sentiment Analysis of Comment Text

In this phase, applying sentiment analysis techniques is performed for the main research target. As previously stated, different approaches could be selected according to the document nature, in this research and according to the literature review that is performed by the authors, SVM is the technique that will be applied in the proposed model.

Performing documents classification for the posts' comments is performed using the lexicon approach in [8]. Mohsen and his colleagues developed an opinion lexicon in [8] that contains 6800 words classified as positive or negative. Then applying cosine similarity for the created vectors is performed with measuring the polarity of each as discussed in previous sections.

C. Calculating the Correlation Coefficient

The Facebook posts are classified to negative or positive according to post's reactions, and each comment on the post is classified by using sentiment analysis.

For each post, the correlation coefficient value is calculated between the results of classification of reactions and comments, targeting to determine if the classification of comments is similar to the classification reactions.

The correlation coefficient is calculated through the following equations: [21] [39].

$$r = \frac{1}{n-1}\left[\frac{\sum_x \sum_y (x-\bar{x})(y-\bar{y})}{S_x\, S_y}\right]$$

The overall results give an indication of the post credibility according to the degree of similarity between comments and reactions.

IV. Experimental Results

An example for the model process is as follows:

Post A has the values illustrated in table I:

Total number of Negative reactions=

Sad (140) + Angry (195) = 335

Total number of Positive reactions =

Love (91) + Wow (35) + Haha (28) =154

Percentage of Negative =

$$\frac{\text{(Total Number of negative)}}{\text{(Total Number of reactions)}}\ X\ 100 = 68.50$$

Percentage of Positive =

$$\frac{\text{(Total Number of positive)}}{\text{(Total Number of reactions)}}\ X\ 100 = 31.49$$

TABLE I. POST'S REACTIONS EXAMPLE

Like	**Love**	**Wow**	**Haha**	**Sad**	**Angry**
250	91	35	28	140	195

Then the post is classified to be Negative

The comment classification is classified according to the vector space model by measuring the similarity. The lexicon contains 6800 words classified as positive or negative with the ability for enrichment as discussed in [8]. Each class is considered as a document, and the comment is also considered as a document. Then the similarity between the comment and each document class, the higher value is the classified class.

For example, a comment state that: "it is a bad product."

After applying text preprocessing, there are two extracted words: bad and product, and the result shown in table II.

These results are calculated for each post as illustrated in table III.

TABLE II. COMMENT CLASSIFICATION EXAMPLE

Comment ID	**Negative**	**Positive**	**Result**
1423_25	1	0	Positive

TABLE III. POST CLASSIFICATION EXAMPLE

Post ID	**Negative comments**	**Positive comments**	**Result**
1423	258	349	Positive

V. Evaluation

Although the experimental phase in researches can use benchmark resources [40] [41] [42] [43] [44], however, applying the proposed approach on a real case highly prove the approach effectiveness [45] [46] [47] [48].

The dataset sample followed the research in [49] [50]for selecting the suitable sampling technique. It was collected, like the following:

The research focused on 8 Facebook pages News agencies and 21 posts selected from the Facebook pages shown in table IV.

Each post has a number of comments; a total number of comments in the dataset is **1523**. For each post, we collected the emoji, and the polarity classification is calculated as shown in table V and table VI. For the comments the polarity classification is calculated, fig. 2 shows the distribution of classes for each post, the classes are positive, negative and neutral. The post was classified according to the biggest value of the three classes for the comments.

TABLE IV. FACEBOOK PAGES AND SELECTED POSTS

No	Facebook News Page	Number of selected posts
1	BBC News	3
2	BBC Family News	3
3	CBS News	3
4	NBC News	3
5	NPR news	3
6	Politico	2
7	NY Daily News	2
8	Democratic Underground	2

TABLE V. POSTS WITH THEIR EMOJI

ID	Facebook Page_ Post ID	Angry	Ha-ha	Like	Love	Sad	Wow	Positive	Negative	Sentiment
1	228735667216_ 10154890879532217	54	24	993	144	12	24	192	66	POSITIVE
2	228735667216_ 10154890968202217	172	8	994	11	783	264	283	955	NEGATIVE
3	228735667216_ 10154890852247217	5	12	2034	369	6	45	426	11	POSITIVE
4	228735667216_ 1426789250735491	6	0	2262	754	1989	11	765	1995	NEGATIVE
5	228735667216_ 10154890645702217	65	513	4336	54	128	815	1382	193	POSITIVE
6	228735667216_ 10154890600247217	25	136	2549	195	2	17	348	27	POSITIVE
7	228735667216_ 10154890480662217	0	2	4123	1005	2256	41	1048	2256	NEGATIVE
8	228735667216_ 10154890399087217	51	273	1302	24	39	190	487	90	POSITIVE
9	228735667216_ 1887717684813716	403	10	2169	15	874	115	140	1277	NEGATIVE
10	228735667216_ 10154889414912217	745	1	1374	16	722	106	123	1467	NEGATIVE
11	228735667216_ 10154889386187217	4	8	2667	195	729	9	212	733	NEGATIVE
12	228735667216_ 10154889308562217	153	7	983	10	323	12	29	476	NEGATIVE
13	228735667216_ 10154889223727217	626	70	747	23	28	25	118	654	NEGATIVE
14	228735667216_ 10154889016422217	3	47	11024	1120	24	2531	3698	27	POSITIVE
15	228735667216_ 10154888875107217	3	1117	3488	64	36	602	1783	39	POSITIVE
16	228735667216_ 10154888663672217	2	8	3644	335	1	59	402	3	POSITIVE
17	228735667216_ 10154888522807217	5356	4235	5455	214	259	1231	5680	5615	POSITIVE
18	228735667216_ 10154888481772217	5886	253	8299	163	948	1440	1856	6834	NEGATIVE
19	228735667216_ 10154888328917217	289	34	1075	52	13	36	122	302	NEGATIVE
20	228735667216_ 10156521638374968	2	75	811	17	23	231	323	25	POSITIVE
21	228735667216_ 10155178616101971	285	3941	11194	175	66	4830	8946	351	POSITIVE

TABLE VI. POST'S COMMENTS WITH THEIR SENTIMENT ANALYSIS

ID	Facebook Page Post ID	message	Sentiment
1	228735667216_ 10154890879532217	We are speaking to NRA supporters as well as Women's March supporters	POSITIVE
2	228735667216_ 10154890879532217	If you are just joining us, we are outside of the headquarters of the National Rifle Association outside of Washington DC. The Women's March are demonstrating and then marching to the Department of Justice to protest a controversial commercial.	NEGATIVE
3	228735667216_ 10154890879532217	Do you know how backward America is in allowing people to have guns? Nineteen kids per day die in the USA by accidental shootings... Constitutional rights! Get a grip.	NEGATIVE
4	228735667216_ 10154890879532217	People who legally own guns often seem all too eager for an opportunity to shoot someone. Statistics show that guns bought 'for protection' very rarely get used as intended. Ask any ER doctor.	NEGATIVE

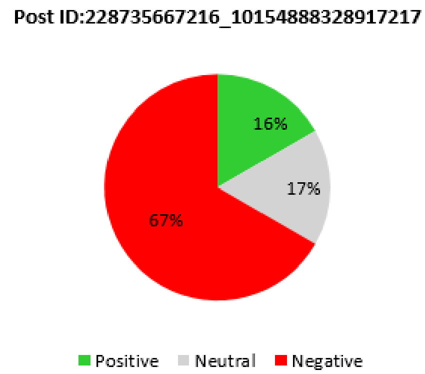

Fig. 2. Pie Chart of Post's Comments Classification.

Table VII shows the posts polarity according to their comments for the specific Facebook page. The final step targets to calculate the credibility score by measuring the correlation coefficient between the Facebook emoji reactions on the post and the polarity of the comments on the same post, the degree of matching between the emoji reactions and polarity of comments represents the degree of credibility of Facebook post as shown in table VIII.

TABLE VII. FACEBOOK PAGE'S COMMENTS POLARITY

ID	Facebook Page_ Post ID	Positive	Negative	Sentiment
1	228735667216_ 10154888328917217	2	8	NEGATIVE
2	228735667216_ 10154888481772217	8	8	NEGATIVE
3	228735667216_ 10154888522807217	16	8	POSITIVE
4	228735667216_ 10154888663672217	54	18	POSITIVE
5	228735667216_ 10154888875107217	58	38	POSITIVE
6	228735667216_ 10154889016422217	72	26	POSITIVE
7	228735667216_ 10154889223727217	8	12	NEGATIVE
8	228735667216_ 10154889308562217	40	30	POSITIVE
9	228735667216_ 10154889386187217	26	8	POSITIVE
10	228735667216_ 10154889414912217	16	46	NEGATIVE
11	228735667216_ 10154890399087217	44	42	POSITIVE
12	228735667216_ 10154890480662217	63	30	POSITIVE
13	228735667216_ 10154890600247217	35	47	NEGATIVE
14	228735667216_ 10154890645702217	44	43	POSITIVE
15	228735667216_ 10154890852247217	66	12	POSITIVE
16	228735667216_ 10154890879532217	31	50	NEGATIVE
17	228735667216_ 10154890968202217	27	53	NEGATIVE
18	228735667216_ 10155178616101971	6	4	POSITIVE
19	228735667216_ 10156521638374968	40	34	POSITIVE

The value of negative for the post is replaced with (-1), and the value of positive is replaced with (+1) for calculating the correlation coefficient.

The correlation coefficient for the values in table VIII is calculated to be 0.337099931.

The correlation coefficient value is between 0 to 1 according to the strength or similarity between the two variables.

The credibility rank of the previous posts for the Facebook page as a percentage is: 0.3371 * 100 = 33.71 %

So the rule extracted from previous calculations is:

The Posts of a Facebook page with ID (228735667216) is 33.71 %

After reviewing the presented example with experts, it is confirmed that that the results shown is related to the post status. Therefore, after applying the proposed model to the collected dataset and reviewing the results with an expert, the proposed model is found to have an accuracy of 95% for detecting the News' credibility. However, more investigation was required for manipulating the abnormality to increase the accuracy.

Credibility percentage increases the share and use of the UGC contents that it is probably credible, and at the same time, it ignores the UGC that it is not probably credible. Many enhancements could be applied to increase the accuracy of the model, like applying deeper data mining or machine learning techniques, which will be our target for future work.

TABLE VIII. FACEBOOK PAGE (228735667216) POSTS' ANALYSIS

ID	Post ID	Emoji	Comment	Emoji	Comment
1	10154888328917217	NEGATIVE	NEGATIVE	-1	-1
2	10154888481772217	NEGATIVE	NEGATIVE	-1	-1
3	10154888522807217	POSITIVE	POSITIVE	1	1
4	10154888663672217	POSITIVE	POSITIVE	1	1
5	10154888875107217	POSITIVE	POSITIVE	1	1
6	10154889016422217	POSITIVE	POSITIVE	1	1
7	10154889223727217	NEGATIVE	NEGATIVE	-1	-1
8	10154889308562217	NEGATIVE	POSITIVE	-1	1
10	10154889414912217	NEGATIVE	NEGATIVE	-1	-1
11	10154890399087217	POSITIVE	POSITIVE	1	1
12	10154890480662217	NEGATIVE	POSITIVE	-1	1
13	10154890600247217	POSITIVE	NEGATIVE	1	-1
14	10154890645702217	POSITIVE	POSITIVE	1	1
15	10154890852247217	POSITIVE	POSITIVE	1	1
16	10154890879532217	POSITIVE	NEGATIVE	1	-1
17	10154890968202217	NEGATIVE	NEGATIVE	-1	-1
18	10155178616101971	POSITIVE	POSITIVE	1	1
20	1426789250735491	NEGATIVE	POSITIVE	-1	1
21	1887717684813716	NEGATIVE	POSITIVE	-1	1

VI. CONCLUSION AND FUTURE DIRECTIONS

Social Network is a main source of News which leads to the extreme importance for these sources. However, it is a fact that it is also considered a gate to rumors. The users' reaction is a central factor for spreading the News either it is real of Fake. Therefore, this research focused on measuring the News' credibility in Social media in general and on Facebook in specific. The proposed model was based on three main pillars, an enrichment sentiment lexicon approach, a sentiment analysis approach, and determining correlations. The proposed model considered both the users comments and emotions. The main idea was relating the post contents with the users' response. The results showed the success of the proposed model, however, it only included text comments, and it needs to include other types of comments including images. Moreover, the paper only included English language, therefore, including multilingual component to the proposed approach is one of the key factors in the future directions. A future direction was to improve the accuracy level by considering an enhancement to the SVM approach as well as including the users' trend in their reactions by applying a semantic network that relates between the News networks with the users' network.

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