



An Emotional Analysis of False Information in Social Media and News Articles

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Fake news is risky, since it has been created to manipulate readers' opinions and beliefs. In this work, we compared the language of false news to the real one of real news from an emotional perspective, considering a set of false information types (propaganda, hoax, clickbait, and satire) from social media and online news article sources. Our experiments showed that false information has different emotional patterns in each of its types, and emotions play a key role in deceiving the reader. Based on that, we proposed an LSTM neural network model that is emotionally infused to detect false news.

CCS Concepts: • **Computing methodologies** → *Neural networks*; **Natural language processing**;

Additional Key Words and Phrases: Fake news, suspicious news, false information, emotional analysis

ACM Reference format:

Bilal Ghanem, Paolo Rosso, and Francisco Rangel. 2020. An Emotional Analysis of False Information in Social Media and News Articles. *ACM Trans. Internet Technol.* 20, 2, Article 19 (April 2020), 18 pages.
<https://doi.org/10.1145/3381750>

1 INTRODUCTION

With complicated political and economic situations in many countries, some agendas are publishing suspicious news to affect public opinions regarding specific issues [23]. The spreading of this phenomenon is increasing recently with the large usage of social media and online news sources. Many anonymous accounts in social media platforms start to appear, as well as new online news agencies without presenting a clear identity of the owner. Twitter has recently detected a campaign¹ organized by agencies from two different countries to affect the results of the last U.S. presidential elections of 2016. The initial disclosures by Twitter have included 3,841 accounts.

¹https://blog.twitter.com/official/en_us/topics/company/2018/enabling-further-research-of-information-operations-on-twitter.html.

The work of the second author was partially funded by the Spanish MICINN under the research project MISFIS-FAKENHATE on Misinformation and Miscommunication in social media: FAKENews and HATE speech (PGC2018-096212-B-C31).

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1533-5399/2020/04-ART19 \$15.00

<https://doi.org/10.1145/3381750>

A similar attempt was done by Facebook, as they detected coordinated efforts to influence U.S. politics ahead of the 2018 midterm elections.²

False information is categorized into eight types,³ according to Reference [39]. Some of these types are intentional to deceive where others are not. In this work, we are interested in analyzing four main types, i.e., **hoaxes**, **propaganda**, **clickbait**, and **satire**. These types can be classified into two main categories—misinformation and disinformation—where misinformation considers false information that is published without the intent to deceive (e.g., satire). Disinformation can be seen as a specific kind of false information with the aim to mislead the reader (e.g., hoax, propaganda, and clickbait). **Propaganda** is a fabricated story spread to harm the interest of a particular party. **Hoaxes** are similar to propaganda, but the main aim of the writer is not to manipulate the readers' opinions but to convince them of the validity of a paranoia-fueled story [32]. **Clickbait** is another type of disinformation that refers to the deliberate use of misleading headlines, thumbnails, or stories' snippets to redirect attention (for traffic attention). **Satire** is the only type of misinformation, where the writer's main purpose is not to mislead the reader, but rather to deliver the story in an ironic way (to entertain or to be sarcastic).

The topic of fake news is gaining attention due to its risky consequences. A vast set of campaigns has been organized to tackle fake news. The owner of Wikipedia encyclopedia created the news site WikiTribune⁴ to encourage evidence-based journalism.

Another way of addressing this issue is by fact-checking websites. These websites such as *politifact.com*, *snopes.com*, and *factchecking.org* aim to debunk false news by manually assessing the credibility of claims that have been widely circulated in online platforms. These campaigns were not limited to the English language, where other languages such as Arabic have been targeted by some sites like *fatabyyano.net*.⁵

Hypothesis. Trusted news is recounting its content in a naturalistic way without attempting to affect the opinion of the reader. However, false news is taking advantage of the presented issue sensitivity to affect readers' emotions, which sequentially may affect their opinions as well. A set of works has been done previously to investigate the language of false information. The authors in Reference [37] have studied rumors in Twitter. They have investigated a corpus of true and false tweet rumors from different aspects. From an emotional point of view, they found that false rumors inspired fear, disgust, and surprise in their replies while the true ones inspired joy and anticipation. Some kinds of false information are similar to other language phenomena. For example, satire by its definition showed similarity with irony language. The work in Reference [12] showed that affective features work well in the detection of irony. In addition, they confirmed that positive words are more relevant for identifying sarcasm and negative words for irony [38]. The results of these works motivate us to investigate the impact of emotions on false news types. These are the research questions we aim to answer:

RQ1. *Can emotional features help detect false information?*

RQ2. *Do the emotions have similar importance distributions in both Twitter and news article sources?*

RQ3. *Which of the emotions have a statistically significant difference between false information and truthful ones?*

²<https://www.businessinsider.es/facebook-coordinated-effort-influence-2018-us-midterm-elections-2018-7>.

³Types of false information: fabricated, propaganda, conspiracy theories, hoaxes, biased or one-sided, rumors, clickbait, and satire news.

⁴<https://www.wikitribune.com>.

⁵fatabyyano is an Arabic term that means "to make sure."

RQ4. *What are the top-N emotions that discriminate false information types in both textual sources?*

In this work, we investigate suspicious news in two different sources: Twitter and online news articles. Concerning the news articles source, we focus on the beginning part of them, since they are fairly long, and the emotional analysis could be biased by their length. We believe that the beginning part of false news articles can present a unique emotional pattern for each false information type, since the writer in this part is normally trying to trigger some emotions in the reader.

Throughout the emotional analysis, we go beyond the superficial analysis of words. We hope that our findings in this work will contribute to fake news detection.

The key contributions of this article are:

- **Model:** We propose an approach that combines emotional information from documents in a deep neural network. We compare the obtained results with a set of baselines. The results show that our approach is promising.
- **Analysis:** We show a comprehensive analysis on two false information datasets collected from social media and online news articles, based on a large set of emotions. We compare the differences from an affective perspective in both sources and obtain valuable insights on how emotions can contribute to detect false news.

The rest of the article is structured as follows: After a brief review of related work in Section 2, Section 3 introduces our emotionally infused model. Then, we present the evaluation framework in Section 4. Section 5 reports the experiments and the results, followed by an analysis on the false information types from an emotional perspective in Section 6. The conclusions of this work are summarized in Section 7.

2 RELATED WORK

The work that has been done previously on the analysis of false information is rather small regarding the approaches that were proposed. In this section, we present some recent works on language analysis and detection of false information.

Recent attempts tried to analyze the language of false news to give a better understanding. A work done in Reference [36] has studied the false information in Twitter from a linguistic perspective. The authors found that real tweets contain significantly fewer bias markers, hedges, subjective terms, and less harmful words. They also found that propaganda news targets morals more than satires and hoaxes but less than clickbaits. Furthermore, satirical news contains more loyalty and fewer betrayal morals compared to propaganda. In addition, they built a model that combined a set of features (graph-based, cue words, and syntax) and achieved a good performance comparing to other baselines (71% vs. 59% macro-F1). Another similar work [32] has been done to characterize the language of false information (propaganda, hoax, and satire) in online news articles. The authors have studied the language from different perspectives: the existence of weak and strong subjectivity, hedges, and the degree of dramatization using a lexicon from Wiktionary. As well, they employed in their study the LIWC dictionary to exploit the existence of personal pronouns, swear, sexual, etc. words. The results showed that false news types tend to use first and second personal pronouns more than truthful news. Moreover, the results showed that false news generally uses words to exaggerate (subjectives, superlatives, and modal adverbs) and, specifically, satire uses more adverbs. Hoax stories tend to use fewer superlatives and comparatives, and propaganda uses relatively more assertive verbs. Moving away from these previous false information types, the work in Reference [37] has focused on analyzing rumors in Twitter (from a factuality perspective:

true or false). They analyzed about 126,000 rumors and found that falsehood spreads significantly further, faster, deeper, and more broadly than truth in many domains. In addition, they found that false rumors are more novel than truthful ones, which made people more likely to share them. From an emotional perspective, they found that false rumors triggered “fear,” “disgust,” and “surprise” in replies while truthful ones triggered “anticipation,” “sadness,” “joy,” and “trust.” Another work [17] has studied the problem of detecting hoaxes by analyzing features related to the content in Wikipedia. The work showed that some features such as hoax articles’ length as well as the ratio of wiki markups (images, references, links to other articles and to external URLs, etc.) are important to discriminate hoaxes from legitimate articles. Many approaches have been proposed on fake news detection. In general, they are divided into social media and news claims-based approaches. The authors in References [16, 20, 29, 34, 40] have proposed supervised methods using recurrent neural networks or by extracting manual features such as a set of regular expressions, content-based, network-based, and so on. As an example, the work by Reference [3] assessed the credibility of tweets by analyzing trending topics. They used message-based, user-based, and propagation-based features, and they found that some features related to user information such as user’s age, number of followers, status counts, and so on, have helped the most to discriminate truthful from deceitful tweets. Other news claims-based approaches [9, 14, 18, 26, 27] have been mainly focusing on inferring the credibility of the claims by retrieving evidence from Google or Bing search engines. These approaches have employed a different set of features starting from manual features (e.g., cosine similarity between the claims and the results, Alexa Rank of the evidence source) to a fully automatic approach using deep learning networks. A recent trend started to appear and is trying to approach the detection of fake news from a stance perspective. The aim is to predict how other articles orient to a specific fact [2, 10, 11].

3 EMOTIONALLY INFUSED MODEL

In this section, we describe the Emotionally Infused Network we propose (EIN).

3.1 Emotional Lexicons

Several emotional models well-grounded in psychology science have been proposed, such as the ones by Magda Arnold [1], Paul Ekman [6], Robert Plutchik [25], and Gerrod Parrot [24]. On the basis of each of them, many emotional resources (lexicons) were built in the literature. In this work, we consider several emotional resources to increase the coverage of the emotional words in texts as well to have a wider range of emotions in the analysis. Concretely, we use EmoSenticNet, EmoLex, SentiSense, LIWC, and Empath:

- EmoSenticNet [28] is a lexical resource that assigns WordNet-Affect⁶ emotion labels to SenticNet⁷ concepts. It has a total of 13,189 entries annotated using the six Ekman’s basic emotions.
- EmoLex [22] is a word-emotion association lexicon that is labeled using the eight Plutchik’s emotions. This lexicon contains 14,181 words.
- SentiSense [5] is a concept-based affective lexicon that attaches emotional meanings to concepts from the WordNet⁸ lexical database. SentiSense has 5,496 words labeled with emotions from a set of 14 emotional categories, which is an edited version of the merge between Arnold, Plutchik, and Parrott models.

⁶<http://wndomains.fbk.eu/wnaffect.html>.

⁷<https://sentic.net/>.

⁸<https://wordnet.princeton.edu>.

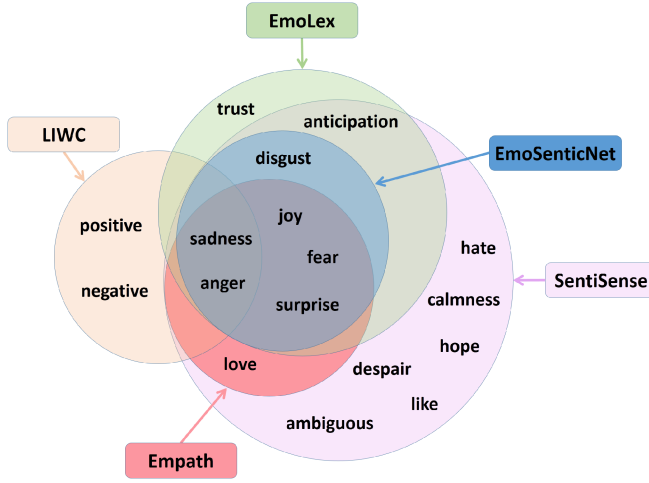


Fig. 1. The emotional lexicons with their own emotions.

- LIWC [35] is a linguistic dictionary that contains 4,500 words categorized to analyze psycholinguistic patterns in text. Linguistic Inquiry and Word Count (LIWC) has four emotional categories: “sadness,” “anger,” “positive emotion,” and “negative emotion.”
- Empath [7] is a tool that uses deep learning and word embeddings to build a semantically meaningful lexicon for concepts. Empath uses Parrott’s model for the emotional representation, but we use only the primary emotions (six emotions) in the Parrott’s hierarchy (“love,” “joy,” “surprise,” “anger,” “sadness,” “fear”).

In our study, we consider the 17 emotions that we show in Figure 1.⁹

3.2 Model

We choose a Long Short-Term Memory (LSTM) [13] that takes the sequence of words as input and predicts the false information type. The input of our network is based on word embedding (content-based) and emotional features (see Figure 2).

3.3 Input Representation

Our network consists of two branches. In the content-based one, we use an embedding layer followed by an LSTM layer. Then, we add an attention layer [30] to make this branch focus on (highlighting) particular words over others.¹⁰ The attention mechanism assigns a weight to each word vector result from the LSTM layer with a focus on the classification class. The input representation for this branch is represented as follows: The input sentence S of length n is represented as $[S_1, S_2, \dots, S_n]$ where $S_n \in \mathbb{R}^d$; \mathbb{R}^d is a d -dimensional word embedding vector of the i th word in the input sentence. The output vectors of the words are passed to the LSTM layer, where the LSTM learns the hidden state h_t by capturing the previous timesteps (past features). The produced hidden state h_t at each time step is passed to the attention layer, which computes a “context” vector c_t as the weighted mean of the state sequence h by:

⁹We investigated the performance of different combinations of lexicons; in the article, we show the results obtained with the best performing combination.

¹⁰We tested our model without the attention layer, but we got a lower result.

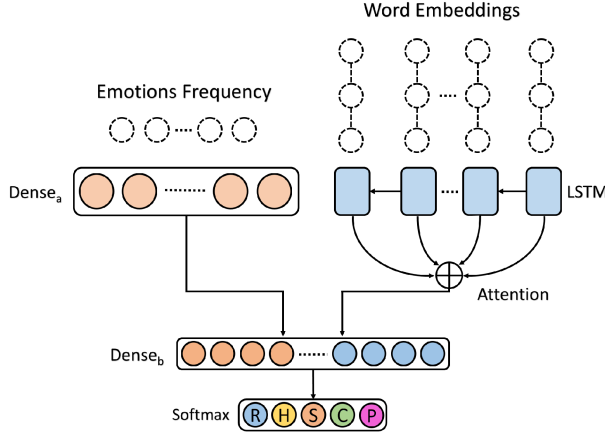


Fig. 2. Emotionally infused neural network architecture for false information detection. RHSCP in the Softmax layer stands for Real, Hoax, Satire, Clickbait, and Propaganda, respectively.

$$c_t = \sum_{t=1}^T \alpha_t h_t, \quad (1)$$

where T is the total number of timesteps in the input sequence, and α_t is a weight computed at each time step t for each state h_t . This output vector is then concatenated with the output from the $dense_a$ (see Figure 2) layer and passed to the $dense_b$ layer, which precedes a final Softmax function to predict the output classes, since the content-based branch is concatenated with the other emotional-based branch.

However, the input representation for the emotional-based branch is defined as follows: Each lexicon is represented as L_{nm} where n is the number of emotional lexicons ($n \in [1, 5]$), and m is the number of emotion categories used depending on the emotion model (e.g., Plutchik, Arnold). In our implementation, the emotional vector of a Lexicon L_{nm} is built using word frequency and normalized by the input sentence's length. Each input sentence is represented using Equation (2):

$$v = L_{1m} \oplus L_{2m} \oplus L_{3m} \oplus L_{4m} \oplus L_{5m}, \quad (2)$$

where $v \in \mathbb{R}^q$, \oplus denotes the concatenate operation, and q is defined in Equation (3):

$$q = \sum_{i=1}^n ||L_i E_M||, \quad (3)$$

Next, the built emotion vector is fed to a dense layer to obtain emotion-specific representations of each input document (Equation (4)):

$$a = f(W_a v + b_a), \quad (4)$$

where W_a and b_a are the corresponding weight matrix and bias terms, and f is an activation function, such as *ReLU*, *tanh*, and so on.

4 EVALUATION FRAMEWORK

4.1 Datasets

Annotated data are a crucial source of information to analyze false information. Current status of previous works lacks available datasets of false information, where the majority of the works focus on annotating datasets from a factuality perspective. However, to analyze the existence of

Table 1. News Articles and Twitter Datasets' Statistics

Category	News Articles	Twitter
Satire	5,750 (18%)	12,502 (8%)
Hoax	5,750 (18%)	6,247 (4%)
Propaganda	5,750 (18%)	66,225 (43.5%)
Clickbait	5,750 (18%)	36,103 (23.5%)
Real News	8,550 (28%)	30,949 (21%)
Total	31,550	152,026

emotions across different sources of news, we rely on two publicly available datasets and a list contains suspicious Twitter accounts.

News Articles. Our dataset source of news articles is described in Reference [32]. This dataset was built from two different sources: For the trusted news (real news), they sampled news articles from the English Gigaword corpus. For the false news, they collected articles from seven different unreliable news sites. These news articles include satires, hoaxes, and propaganda but not clickbait. Since we are interested also in analyzing clickbait, we slice a sample from an available clickbait dataset called Stop_Clickbait [4] that was originally collected from two sources: Wikinews articles' headlines and other online sites that are known to publish clickbait. The satire, hoax, and propaganda news articles are considerably long (some of them reach the length of 5K words). This length could affect the quality of the analysis, as we mentioned before. We focus on analyzing the initial part of the article. Our intuition is that it is where emotion-bearing words will be more frequent. Therefore, we shorten long news articles into a maximum length of N words ($N=300$). We choose the value of N based on the length of the shortest articles. Moreover, we process the dataset by removing very short articles, redundant articles, or articles that do not have a textual content.¹¹

Twitter. For this dataset, we rely on a list of several Twitter accounts for each type of false information from Reference [36]. This list was created based on public resources that annotated suspicious Twitter accounts. The authors in Reference [36] have built a dataset by collecting tweets from these accounts and they made it available. For the real news, we merge this list with another 32 Twitter accounts from Reference [15]. In this work, we could not use the previous dataset¹² and we decide to collect tweets again. For each of these accounts, we collected the last M tweets posted ($M=1000$). By investigating these accounts manually, we found that many tweets just contain links without textual news. Therefore, to ensure the quality of the crawled data, we chose a high value for M (also to have enough data). After the collecting process, we processed these tweets by removing duplicated, very short tweets, and tweets without textual content. Table 1 shows a summary for both datasets.

4.2 Baselines

Emotions have been used in many natural language processing tasks and haveshown their efficiency [31]. We aim at investigating their efficiency to detect false information. In addition to EIN, we created a model (Emotion-based Model) that uses emotional features only by converting the input documents into vectors of emotions frequency (see Equation (2)) and compare it to two

¹¹E.g., "BUYING RATES US 31.170..."

¹²Due to Twitter terms of use, the authors provided in their dataset the IDs of the tweets, and when we tried to collect these tweets many of them were deleted.

Table 2. The Results of the Emotion-based Model with the Emotional Features Comparing to the Baselines

	Accuracy	Macro-Precision	Macro-Recall	Macro-F1
News Articles				
Majority Class	0.34	0.07	0.20	0.10
Random Selection	0.21	0.21	0.21	0.20
Emotion-based Model	0.50	0.48	0.51	0.48
Twitter				
Majority Class	0.44	0.09	0.20	0.12
Random Selection	0.20	0.20	0.20	0.18
Emotion-based Model	0.52	0.55	0.38	0.41

baselines. Our aim is to investigate if the emotional features can independently detect false news. The two baselines of this model are Majority Class baseline (MC) and the Random selection baseline (RAN).

For the EIN model, we compare it to different baselines: **(a)** The first one is Bag-Of-Words with a Support Vector Machine classifier (BOW-SVM). We test different classifiers, and we choose SVM, since it gives the highest result in the 10-fold Cross Validation (CV); **(b)** We use another baseline that is based on word embeddings where for each input document we extract an average word embedding vector by taking the mean of the embeddings for the document's words. Similarly, we test different classifiers and the Logistic Regression classifier shows the best performance (WE-LR); **(c)** The last baseline is the same as our neural architecture but without the emotional features branch: an LSTM layer followed by attention and dense layers.

5 EXPERIMENTS AND RESULTS

5.1 Emotion-based Model

In our experiments, we use 20% of each of the datasets for testing, and we apply 10-fold CV on the remaining part for selecting the best classifier as well for tuning it. We tested many classifiers and we finally chose Random Forest for both datasets, since it obtained the best results.¹³ Table 2 presents the classification results on both datasets.

The results in both datasets show that emotional features clearly detect false news, compared to the baselines (**RQ1**). The emotional features perform better in the news articles dataset compared with these of tweets. We are interested in investigating also how good are the emotional features in detecting each class compared to the RAN baseline. We chose the RAN baseline, since it shows better results with regard to macro-F1 score. For doing so, we investigated the True Positive (TP) classification ratio for each class in each dataset.

The clickbait class shows the highest TPs compared to the other classes. From this, we can infer that clickbaits exploit emotions much more than the other classes to deceive the reader. It is worth mentioning that for the hoax class the proposed approach is better than the random baselines with a small ratio (4% difference). This could be justified by the fact that hoaxes, by definition, try to convince the reader of the credibility of a false story. Hence, the writer tries to deliver the story in a normal way without allowing the reader to fall under suspicion. The number of instances related to the false information classes in the news articles dataset is the same. Therefore, there is not a majority class that the classifier can be biased to. This is not the case in the Twitter dataset. For the

¹³The other classifiers that we tested are: support vector machine (testing both kernels), naive Bayes, logistic regression, k-nearest neighbor, and multilayer perceptron.

Table 3. Models' Parameters Used in the Three Datasets
(News Articles, Twitter, Stop_Clickbait)

Parameter	News Articles		Twitter		Stop_Clickbait	
	LSTM	EIN	LSTM	EIN	LSTM	EIN
LSTM units	140	90	180	180	120	120
Dense _a units	–	320	–	100	–	60
Dense _b units	320	60	120	60	260	120
Batch	64	64	64	64	32	32
Activation	relu	relu	relu	relu	tanh	relu
Optimizer	adadelat	adam	adadelat	rmsprop	rmsprop	Adam
Drop _c	0.5	0.5	0.5	0.2	0.2	0.2
Drop _d	0.2	0.1	0.2	0.2	0.2	0.2

LSTM: the third baseline, EIN: Emotionally Infused Network.

Twitter dataset, the dataset is not balanced; therefore, where the results are biased by the majority class (propaganda). But in general, all the classes' TP ratios are larger than the corresponding ones obtained with the RAN baseline. From these results, we can conclude that suspicious news exploits emotions with the aim to mislead the reader. Following, we present the results obtained by the proposed emotionally infused model.

5.2 Emotionally Infused Model

In the neural model, to reduce the computational costs, instead of the CV process, we take another 20% from the training part as a validation set¹⁴ (other than the 20% that is prepared for testing). For the pretrained word embeddings, we use Google News Word2Vec 300-Embeddings¹⁵ in the neural network as well as in the W2V-LR baseline. For the classical machine learning classifiers for the baselines, we use the Scikit-Learn Python library, and for the deep learning network, we use Keras library with Tensorflow as backend. To tune our deep learning network (hyper-parameters), we use the Hyperopt¹⁶ library. And to reduce the effect of overfitting, we use early stopping technique.

In Table 3, we summarize the parameters with respect to each dataset. We have to mention that we use Dropout after the dense layer in the emotional features branch (Drop_c) as well as after the attention layer in the other one (Drop_d) before the concatenation process. Since it is a multiclass classification process, we use categorical cross-entropy loss function. A summary of the models' parameters is presented in Table 3.

Table 4 summarizes the performance of the proposed model in comparison to those obtained by the baselines. We report macro- precision, recall, and F1, including also the metric of accuracy; for comparing the models' results, we consider the macro of metrics, since it shows an averaged result over all the classes. The baselines that we propose clearly show high results, where the LSTM baseline has the best performance in news articles dataset. In Twitter there is a different scenario: The BOW-SVM baseline shows a higher performance with respect to LSTM. We are interested in investigating the reason behind that. Therefore, we checked the coverage ratio of the used embeddings in the Twitter dataset. We have to mention that we excluded stop words during

¹⁴We are forced to use different validation scenarios, because for selecting the best parameters in the classical machine learning Scikit-Learn library, we used the Grid Search technique where CV is the only option for tuning. However, it is too computationally expensive to use CV to tune a deep neural network using a large parameter space.

¹⁵<https://code.google.com/archive/p/word2vec/>.

¹⁶<https://github.com/hyperopt/hyperopt>.

Table 4. Results of the Proposed Model (EIN) vs. the Baselines

	Accuracy	Macro-precision	Macro-recall	Macro-F1
News Articles				
BOW+SVM	0.74	0.72	0.71	0.71
W2V+LR	0.72	0.70	0.70	0.70
LSTM	0.75	0.77	0.74	0.74
EIN	0.80	0.79	0.80	0.79
Twitter				
BOW+SVM	0.63	0.60	0.56	0.57
W2V+LR	0.53	0.49	0.35	0.36
LSTM	0.64	0.65	0.54	0.56
EIN	0.65	0.61	0.59	0.60

representing the input documents using the pre-trained Google News word embeddings.¹⁷ In the news articles dataset, we found that the coverage ratio of the embeddings is around 94%, while in Twitter it is around 70%. Therefore, we tuned the word embeddings during the training process to improve the document's representation, since we have a larger dataset from Twitter. This process contributed with 1.9% on the final macro-F1 results in Twitter (the result without tuning is 0.54), even though the results obtained with the LSTM baseline is still lower than the one obtained with BOW-SVM. This experiment gives us some intuition that the weaker performance on Twitter may be due to the embeddings. Therefore, we tried different embeddings, but none of them improved the result.¹⁸ The second baseline (W2V-LR) proved the same issue regarding the embeddings. The W2V-LR macro-F1 result in the news articles dataset is competitive, where it is much lower in Twitter. The usage of LSTM is twofold: in addition to being a good baseline, it shows also how much the emotional features contribute in the emotionally infused network.

EIN results outperform the baselines with a large margin (around 3% in Twitter and 6% in news articles), especially in the news articles dataset. The margin between EIN and the best baseline is lower in the Twitter dataset. The results also show that combining emotional features clearly boosts the performance. We can figure out the improvement by comparing the results of EIN to LSTM. EIN shows superior results in news articles dataset with regard to the LSTM (0.79). A similar case appears in the Twitter dataset but with a lower margin (0.60). The results of EIN in Twitter dataset show that emotional features help the weak coverage of word embeddings to improve the performance as well as to overcome the BOW-SVM baseline.

Furthermore, to investigate the improvement that the emotions produced in the detection of the classes, in Table 5, we present the F1 score results for each class. For the news articles dataset, the results show that employing emotions in the EIN model improves the detection in all the cases, especially in real news, propaganda, and satire classes. However, for the Twitter dataset, emotions contribute especially in the case of clickbait and satire.

We observed before that clickbait TP's ratio of the news articles dataset is the highest one, and this result points out that the clickbait class is less difficult to detect specifically from an emotional perspective. Therefore, to assess how our model separates false information types, we employ dimensionality reduction using t-distributed Stochastic Neighbor Embedding (T-SNE) technique [21] to project the document's representation from a high dimensional space to a 2D plane. Thus,

¹⁷The existence of stop words is important to conserve the context in the LSTM network, but we got better results without them.

¹⁸E.g., Glove (using multiple embedding dimensions) and FastText.

Table 5. F1 Score Results of the Proposed Model (EIN) vs. the Baselines with Respect to Each Class

	clickbait	hoax	propaganda	real news	satire
News Articles					
BOW+SVM	0.90	0.54	0.59	0.84	0.66
W2V+LR	0.85	0.57	0.66	0.83	0.57
LSTM	0.88	0.67	0.65	0.80	0.68
EIN	0.91	0.69	0.75	0.85	0.76
Twitter					
BOW+SVM	0.49	0.40	0.70	0.67	0.62
W2V+LR	0.32	0.07	0.66	0.45	0.32
LSTM	0.48	0.35	0.72	0.65	0.63
EIN	0.53	0.37	0.74	0.67	0.67

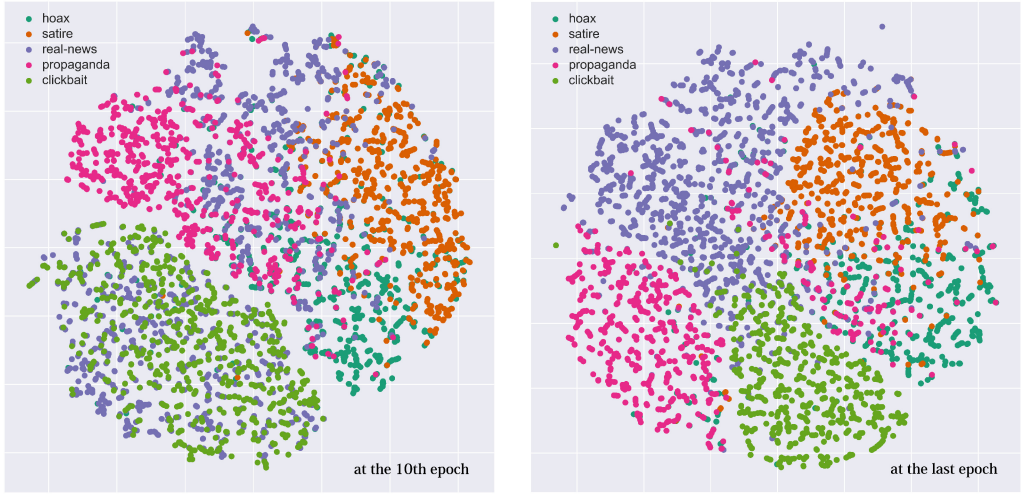


Fig. 3. Projection of documents representation from the news articles dataset.

we project the embeddings in EIN by extracting them from the outputs of Dense₆ layer (see Figure 3). We extract the embeddings twice: once from a random epoch (epoch 10) at the beginning of the training phase, and the other at the last epoch.

Our aim from the early epoch projection is to validate what we have noticed: The clickbait class is less difficult to detect with regard to the other classes. As we can notice in the 10-epoch plot, the clickbait class needs few epochs to be separated from the other types, and this supports what we found previously in the manual investigation of the classes' TP ratios. Despite this clear separation, there is still an overlapping with some real-news records. These results point out that emotions in clickbait play a key role in deceiving the reader. Also, the figure shows that the disinformation classes still need more training epochs for better separation. Real-news records are totally overlapped with the false information classes as well as the false information classes with each other. However, for the last epoch, clearly, the classes are separated from each other and the more important, from the real news. But generally, there still a small overlapping between satires and hoaxes as well few records from the propaganda class.

Table 6. The Performance of EIN on the Clickbaits Dataset Using 10-fold CV

	Accuracy	Precision	Recall	F1
Stop_Clickbait	0.93	0.95	0.90	0.93
LSTM	95	0.95	0.96	0.95
EIN	0.96	0.96	0.97	0.96

5.3 EIN as Clickbaits Detector

From the previous results in Section 5.1 as well as from what we notice in Figure 3, EIN obtains a clear separability of the clickbait class. These observations motivate us to investigate EIN as clickbait detector. Concretely, we test EIN on the source of our clickbait instances [4] in the news articles dataset. As we mentioned previously, this dataset originally was built using two different text sources. For clickbait, the authors have manually identified a set of online sites that publish many clickbait articles. Whereas for the negative class, they collected headlines from a corpus of Wikinews articles collected in other research work. They took 7,500 samples from each class for the final version of the dataset. The authors also proposed a clickbait detector model¹⁹ that employed a combination of features: *sentence structure* (sentence length, average length of words, the ratio of the number of stop words to the number of thematic words, and the longest separation between the syntactically dependent words), *word patterns* (presence of cardinal number at the beginning of the sentence, presence of unusual punctuation patterns), *clickbait language* (presence of hyperbolic words, common clickbait phrases, internet slangs, and determiners), and *N-grams features* (word, Part-Of-Speech, and syntactic n-grams). Using this set of features group, the authors tested different classifiers where SVM showed the state-of-the-art results. They considered Accuracy, Precision, Recall, and F1 to compare their approach to a baseline (an online web browser extension for clickbait detection called Downworthy²⁰).

In this experiment, we consider the third baseline (LSTM) to observe the improvement of the emotional features in the EIN model. Different from the previous experiments, this is a binary classification task. Therefore, we use binary cross-entropy as loss function and we change the Softmax layer to a Sigmoid function. The new parameters for both LSTM and EIN models are mentioned in Table 3.

In Table 6, we present the results of the Stop_Clickbait approach, LSTM baseline, and the EIN model. The results show that our baseline outperforms the proposed clickbait detector with a good margin. Furthermore, the results of the EIN are superior to the LSTM and the Stop_Clickbait detector. Considering emotions in the EIN deep learning approach improved the detection of false information. This is due to the fact that in clickbait, emotions are employed to deceive the reader.

6 DISCUSSION

The results show that the detection of suspicious news in Twitter is harder than detecting it in news articles. Overall, the results of EIN showed that emotional features improve the performance of our model, especially in the case of the news articles dataset. We manually inspected the Twitter dataset and observed that the language of the tweets has differences compared to the news articles one. We found that news in Twitter has many abbreviations (amp, wrt, JFK...etc.), bad word abbreviations (WTF, LMFO...etc.), informal language presentation, and typos. This reduces the coverage ratio of word embeddings. We also noticed that suspicious news in Twitter are more related to

¹⁹We use Stop_Clickbait to refer to this approach in the rest of the experiments.

²⁰<http://downworthy.snipe.net/>.

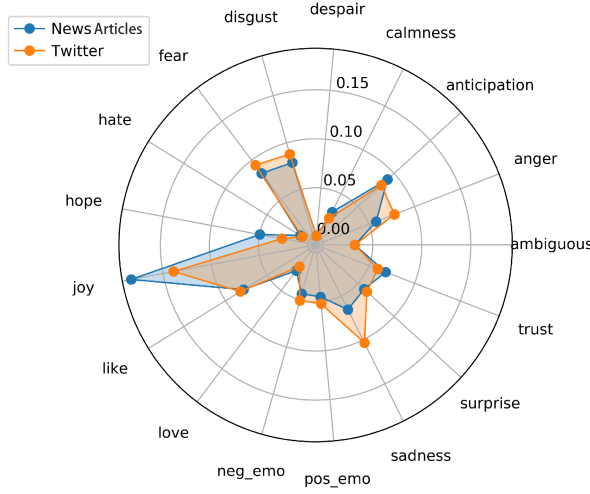


Fig. 4. Best ranked features according to Information Gain.

sexual issues. To validate our observations, we extracted the mean value of sexual words using a list of sexual terms [8]. The mean value is the average number of times a sexual/bad word appears in a tweet normalized by the length of the tweet. The mean value in Twitter is 0.003²¹ while in news articles it is 0.0024. Similarly, suspicious news in Twitter presented more insulting words²² than in news articles, where the mean value in Twitter is 0.0027 and 0.0017 in news articles.

Following, we focus on analyzing false information from an emotional perspective. We are aiming to answer the rest of the questions, **RQ2**, **RQ3**, and **RQ4**.

RQ2. *Do emotions have similar importance distributions in both Twitter and news article sources?*

Intuitively, the emotions contribution in the classification process is not the same, where some words could manifest the existence of specific kinds of emotions rather than others. To investigate this point, we use Information Gain (IG) to identify the importance of emotions in discriminating between real and all the other types of false news (multiclass task) in both Twitter and news articles datasets (see Figure 4). Before going through the ranking of features importance, we notice that the emotions ranking shapes are very similar in both Twitter and news articles. This states that despite the fact that the language is different, both sources have similar overall emotions distribution. In other words, false news employs a similar emotional pattern in both text sources. Since the news language in Twitter is not presented as clearly as in news articles, this observation can help to build a cross-source system that is trained on suspicious news from news articles to detect the corresponding ones in Twitter. Figure 4 shows also that the emotion “joy” is the most important emotion in both datasets. It also mentions that “despair” and “hate” are almost not used in the classification process. The ranking of the features in both sources is different, where in the news articles dataset the top important emotions are “joy,” “anticipation,” “fear,” and “disgust,” respectively. However, the top ones in Twitter are “joy,” “sadness,” “fear,” and “disgust.”

RQ3. *Which of the emotions have a statistically significant difference between false information and truthful ones?*

We measure statically significant differences using the t-test on emotions across real news and false news (binary task) in both datasets in Figure 5. These findings provide a deeper understanding

²¹The mean value is normalized by the sentence length, since the news articles documents are longer than tweets.

²²Insult-wiki: http://www.insult.wiki/wiki/Insult_List.

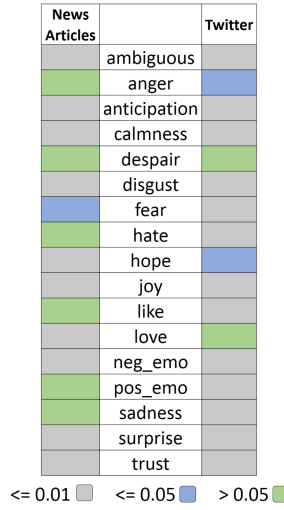


Fig. 5. Statistical significant differences between false and real news on Twitter and news articles datasets using t-test.

Table 7. The Top 3 Most Important Emotions in Each False Information Type

Rank	clickbait	hoax	propaganda	satire
News Articles				
1	surprise	hope	joy	disgust
2	neg_emo	anger	fear	neg_emo
3	like	like	calmness	pos_emo
Twitter				
1	surprise	like	fear	pos_emo
2	neg_emo	disgust	hope	disgust
3	fear	anticipation	calmness	sadness

of the EIN performance. The results show that “joy,” “neg_emo,” “ambiguous,” “anticipation,” “calmness,” “disgust,” “trust,” and “surprise” have significant statistical differences between real and suspicious news in both datasets. Some other emotions such as “despair” and “anger” have no statistical difference in both datasets. It turns out that the results we obtain are generally consistent with the IG results in research question **RQ2**. We notice in the IG analysis that some emotions have a higher importance in one of the news sources: “sadness,” “anger,” and “fear” have a higher importance in Twitter than in news articles, and the opposite for “hope.” We observe the same findings using the t-test.

RQ4. *What are the top-N emotions that discriminate false information types in both textual sources?*

False information types are different in the way they present the news to the reader. This raises a question: What are the top employed emotions in each type of false information? In Table 7, we present the first three²³ emotions that contribute mostly to the classification process to each type. This can indicate to us what emotion types are most used in each type of false information.

²³We used SVM classifier coefficients (linear kernel) to extract the most important emotions to each classification class.

News Articles:

freshman nate washburn was **mutilated** in front of students players....midnight **madness** sacrifice
a freshman....so they can **devour** it as one eruditio et religio following the ritualistic....

....phil zipper was **smacked** into this week by a forceful **blow** delivered by his wife during...after materializing in
a **burst** of swirling colored....of last week's **smack** zipper who....have **hatred** and **prejudice** finally been eradicated....

Twitter:

marine corps adds file to **trash** bin to command climate survey procedures.

nice this guy has podcasts and no **toilet** paper.

florida zoo employee killed while attempting to **rape** alligator.

Fig. 6. Examples from news articles and Twitter datasets trigger the emotion “disgust.”

Table 7 shows that clickbaits express “surprise” and “negative emotion” the most. This validates the definition of clickbait as “attention redirection” by exploiting the reader and convincing him/her that there is an unexpected thing with negative emotion. The result of seeing “fear” in the top features in Twitter is interesting; one recent study presented the hypothesis that says: *curiosity is the best remedy for fear* [19], based on psychological interpretations. Taking into account the definition of clickbait as “attention redirection,” looking at our results, we can prove this hypothesis. Furthermore, despite the language differences in both datasets, we obtain almost the same results, which emphasizes our results. For hoaxes, it is not simple to interpret a specific pattern of emotions in the results. We might justify it by the fact that hoaxes are written to convince the reader of the validity of a story; therefore, the writer is trying to present the story in a normal way (truthful) similar to a real story. Therefore, the top emotions are not unique to the hoax type. But what we find from the top hoax emotions in both datasets is that they are generally different except the emotion “like.” Despite the natural narrative way of presenting the story, the analysis shows that the writer still uses “like” to smoothly grab readers’ attention. Propaganda type has clearer emotional interpretation considering its definition. We find that propaganda expresses “joy,” “fear,” and at the same time “calmness” in the news articles. Both “joy” and “fear” are contrary from an emotional polar perspective, where “joy” shows the extreme of the positive emotions and “fear” the extreme negative; and at the same time, “calmness” is present. The emotional shifting between the two extremes is a clear attempt at opinion manipulation from an emotional perspective. We obtain a similar emotion set from Twitter, but instead of “joy,” we get “hope.” Last, satire is defined as a type of parody presented in a typical format of mainstream journalism, but in a similar way to irony and sarcasm phenomena [33]. The results of the analysis show that “disgust” and “positive emotion” are present in both datasets, but we get “negative emotion” in the news articles and “sadness” in Twitter (both are placed in the negative side of emotions). We are interested in investigating the cause of the emotion “disgust,” which appeared in the results from both datasets. We conduct a manual analysis on the text of the satire type in both datasets to shed some light on the possible causes. We notice that the satire language in the news often employs the emotion “disgust” to give a sense of humor. Figure 6 shows some examples from the news articles dataset, highlighting the words that triggered the emotion “disgust.”

7 CONCLUSIONS AND FUTURE WORK

In this article, we have presented an emotionally infused deep learning network that uses emotional features to identify false information in Twitter and news articles sources. We performed

several experiments to investigate the effectiveness of the emotional features in identifying false information. We validated the performance of the model by comparing it to an LSTM network and other baselines. The results on the two datasets showed that clickbaits have a simpler manipulation language where emotions help detect them. This demonstrates that emotions play a key role in deceiving the reader. Based on this result, we investigated our model performance on a clickbait dataset, and we compared it to the state-of-the-art performance. Our model showed superior results near to 96% F1 value.

Overall results confirmed that emotional features have boosted EIN model performance, achieving better results on three different datasets (**RQ1**). These results emphasized the importance of emotional features in the detection of false information. In Twitter, false news content is deliberately sexually oriented and it uses many insulting words. Our analysis showed that emotions can help detect false information also in Twitter.

In the analysis section, we answered a set of questions regarding the emotions distribution in false news. We found that emotions have similar importance distribution in Twitter and news articles regardless of the differences in the used languages (**RQ2**). The analysis showed that most of the used emotions have statistical significant difference between real and false news (**RQ3**). Emotions play a different role in each type of false information, in line with its definition (**RQ4**). We found that clickbaits try to attract the attention of the reader by mainly employing the “surprise” emotion. Propaganda is manipulation of the feelings of readers by using extreme positive and negative emotions, triggering a sense of “calmness” to confuse the readers and enforce a feeling of confidence. Satire news instead uses the “disgust” emotion to give a sense of humor.

To the best of our knowledge, this is the first work that analyzes the impact of emotions in the detection of false information considering both social media and news articles. As a future work, the results of our approach as a clickbait detector motivates us to develop a clickbait detector as a web browser extension. Also, we will study how the emotions flow inside the articles of each kind of false information, which is worthy to be investigated, as the results of this work confirmed.

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Received July 2019; revised December 2019; accepted January 2020