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Identification of Fake Messages in The Media Based on Their Emotional Coloring

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Abstract

The purpose of this research is to determine the feasibility of identifying fakes based on their emotional tone. The research objective is to develop a methodical approach that allows for the automatic identification of fakes without complex verification procedures using software tools. The method we propose does not involve revolutionary mathematical models but rather compiles existing developments in a specific sequence of procedures, which constitutes its scientific novelty. The advantage of this approach lies in its simplicity and relatively easy application, even for users with basic computer skills. To illustrate and facilitate replication, we provide a research flowchart and a link to the "Orange" program with open-source code. Specifically, the methodology involves calculating emotional probabilities according to Plutchik and classifying messages based on a Random Forest (RF) model, implemented within the mentioned program through widgets.

Keywords: *Fake News, Text Analysis, Neural Network, Social Network, Sentiment.*

INTRODUCTION

Identifying fake news in the media is a well-explored topic within the scientific community. The prevalence of fake news is steadily increasing each year, and what used to be primarily the work of interested individuals has now been amplified by the involvement of neural networks. The quality, diversity, and believability of fake news have reached a point where distinguishing truth from falsehood has become a complex challenge. We are approaching a time when fake news will blur the line that separates truth from fiction.

Consumers of information will no longer be concerned solely with the content itself; instead, they will focus on how the broader community reacts to the news. Consequently, they will make decisions based on these reactions, decisions that could have far-reaching consequences for both the individual and society as a whole. These decisions will carry economic implications, especially for active participants in the stock market, as they choose their investment strategies for their finances or on behalf of clients, which could include legal entities, banks, or large corporations. The ramifications may extend beyond mere financial loss, potentially posing threats as serious as bankruptcy.

In summary, the growing threat of fake news has the potential to disrupt not only the flow of information but also the stability of financial and economic systems, making it a critical challenge that needs to be addressed with urgency.

And if this phenomenon takes on a mass scale, it could trigger a chain reaction, potentially harming entire industries or even the country's economy as a whole. Neural networks are now capable of generating highly convincing fakes, including not only textual content but also graphic elements and even videos. These capabilities were once the domain of well-equipped, large-scale film production companies. What's most concerning is that these technologies are accessible to nearly anyone with a modern smartphone and internet access.

Despite this accessibility, human perception of fakes remains a constant factor. In other words, a neural network must create an emotional backdrop that influences a person to form their own decision, whether it's sharing, commenting, liking/disliking, making trading decisions on the stock market, supporting a public petition, and

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so on. As a result, the "machine" must take into account the psychological basis of such decisions and adapt accordingly.

To identify such fakes, the use of appropriate automated tools is essential, as real-time manual moderation of each message is impractical due to their vast quantity and the rapid spread in social media, a speed unimaginable during the era of print media. The speed of dissemination is one of the most critical factors contributing to societal instability and the information security of modern computer communication systems [Baccianella, S., Esuli, A., & Sebastiani, F. (2010)].

Our research introduces a novel approach for detecting fakes based on emotional assessments of the training dataset, without embedding the text (representing the text corpus in vector form). Instead, we immediately utilize emotional assessments (their probabilities) to build a predictive model. We employ the well-known "Random Forest" tool for model construction. Through a series of tests, we found that this method was the most suitable, as it can work with multiple target variables and does not require additional text corpus manipulations.

Thus, the hypothesis we are testing can be formulated as follows: the emotional profile of fakes can be utilized for their identification without the need for mathematical transformation, relying solely on the assessment of a specific combination of emotional probabilities that differ significantly enough to enable their identification. In other words, formally describing the hypothesis being tested: can we classify the veracity of a given media message with a certain degree of confidence based on its emotional evaluation using a prediction model?

As mentioned earlier, the identification of fakes based on emotions has become a pressing issue in light of the growth of online manipulation and disinformation and has been explored in numerous publications.

In this literature review, we will examine the research findings of scholars in the field of fake news identification. With the rise of social media, there has been a growing interest in analyzing the sentiments of its participants, which is highly valuable in decision-making across various domains and applications. One notable and typical study is the work of Sajjad Jahanbakhsh Gudakahriz, Amir Masoud Eftekhari Moghadam, and Fariborz Mahmoudi (2019). The authors systematically explored a range of models (TF-IDF, LSA, Word2Vec, and Doc2Vec). This article is particularly interesting due to the tools used by the researchers and the results they obtained, which will be considered in our approach assessment.

One of the typical, almost classically presented articles of the last period is the work Alghamdi J, Lin Y, Luo S. (2022). This article discusses the application of deep learning for fake news detection, including the analysis of emotions in the text. The approach outlined assumes the presence of a training dataset to train the model, which will also be employed, but in a version that exclusively relies on the emotional tone of messages as the basis for model training. The article also presents a comprehensive set of well-known models, including “Random Forest” (RF), which consists of decision trees, each trained based on a random set of features (in our case, emotional probabilities).

Another typical article is the work is Vosoughi, S., Roy, D., & Aral, S. (2018). This research explores approaches to detecting fake news in social media by analyzing the emotional tone of messages. The work is particularly intriguing for its systematic exploration of the foundations of fake news detection in traditional and new media, classifying all known methods.

The study by Niroj Ghimire and Surendra Shrestha also involves pre-training with consideration of the semantic relationships between words (2022). S. J. Gudakahriz, A. M. E. Moghadam, & F. Mahmoudi. (2019) highlight the network's accuracy of over 93%. This fact is noteworthy, although it should be noted that the presence of a training dataset may not always align with the research goals.

In the article by G. Güler and S. Gündüz (2023), the issue of fake news detection in social media is studied in both Turkish and English. To address this, they created the first publicly available dataset of Turkish fake and real news tweets called "SOSYalan." For detecting fake news using deep learning, they employed convolutional neural networks and long short-term memory recurrent neural networks. The authors emphasize the superiority of their systems, specifically designed for the Turkish language. This experience is intriguing due to the use of a language that is significantly different from European languages.

The work by Deepak S. and Bhadrachalam Chitturi, (2023), piques interest. The authors rightly point out that deep learning inevitably has limitations and propose an initial stage of real-time data intelligence analysis. They compared the results of models with and without secondary features, as well as explored the effectiveness of various word vector representations for this problem. This approach is intriguing and feasible since news resources generate a substantial amount of metadata, making it possible to even identify sources from which suspicious news frequently originates.

The research by Muhammad Abdul-Mageed and Lyle Ungar is intriguing for our work as the authors have created an extensive and detailed dataset for utilizing emotions in deep learning models (2017). While we may not develop such intricacy, the application of Robert Plutchik's emotions as the basis for our predictive model is undoubtedly interesting.

Stefano Baccianella, Andrea Esuli, and Fabrizio Sebastiani (2010) introduce a publicly available lexical resource, SENTIWORDNET 3.0, annotated for positivity, negativity, and neutrality, and they note a 20% increase in accuracy compared to the previous version.

Bollen, J., Mao, H., & Zeng (2011), in their research, delve into the field of behavioral economics. They explore the correlation between public sentiment and economic indicators, concluding that it is noticeable and can be used for prediction and forecasting. This study interests us primarily for its methodological foundation, as the authors use Twitter.

The work by Arjun Choudhry, Inder Khatri, and Minni Jain (2022) provides a concise overview of known approaches and offers a comparative analysis of methods for emotion classification based on Plutchik's classification and the detection of rumors and fake news in text.

In the article Gilleran, B. (2019), propouse methods for analyzing emotions in texts to combat misinformation are explored. However, the foundation of the research lies in using the original dataset annotated according to an extended list of Plutchik's emotion classes. This work interests because it employs a similar approach, but we use these insights not only for a finer sentiment analysis but also for the identification of fake news in the media.

The study by Li, J., & Xiao, L. (2023), rightly notes that the detection of fake news is based on emotion recognition using a single label. To identify emotions, the authors examined the relationship between truthfulness/position and emotions. This approach is of interest to us because we also use an array of emotions for a more precise reflection of the emotional tone of messages.

Researchers Zhao, Z., Resnick, P., & Mei, Q. (2015) presented a method for detecting trending rumors based on characteristic textual phrases and used them as detectors of rumor clusters. They introduced a methodology based on searching for phrases, grouping similar posts, and then collecting related posts that do not contain these simple phrases.

The segmentation of text into chunks is a crucial aspect of text corpus analysis. In this context, the article by Parsa Kavehzadeh, Mohammad Mahdi Abdollah Pour, and Saeedeh Momtazi, (2021), is noteworthy. In this work, the authors examine well-known models and propose their innovations aimed at extracting more information from the input data compared to other models. Our approach leverages the existing capabilities of text tokenization and other procedures in the program, thereby simplifying the experimentation process and reducing the potential for errors.

Another important aspect of text analysis is the summarization system that could generate concise information based on user queries. Many authors have explored this issue, and in this regard, a recent work by Shima Mehrabi, Seyed Abolghasem Mirroshandel, and Hamidreza Ahmadifar (2020) stands out. In their research, the authors propose a new multilingual summarization system, which is one of the first Persian systems based on deep learning.

Another issue specific to complex languages is the inflection of words based on gender, case, and declension. One drawback of Orange is its primary use of English, so English language corpora are used as training and research datasets. To address this challenge, we have already begun building a Russian dictionary, as Orange allows for its integration as a working resource. In this context, a new work by Ali Hoseinmardy and Saeedeh Momtazi (2020) is of interest. The authors present two different approaches to solving this problem:

Using neural networks for transliteration.

Leveraging available tools used for machine translation/transliteration, such as Google Translate and Behnevis.

This is a highly interesting study, and its results will undoubtedly be used in our further research.

References to several review articles are provided as well, such as Zhang, L., Wang, S., & Liu, B., (2018) by Zubiaga, A., & Ji, H. (2014); Van den Burg, G. J. J., & Groenen, P. J. F. (2016)., Denault, V., Plusquellec, P., Jupe, L. M., St-Yves, M., Dunbar, N. E., Hartwig, M., Koppen, P. J. V. (2020), and several others that provide overviews and analyses of various emotion analysis methods for detecting fake news.

METHODS

The methodology presented in this research may not contain fundamentally new approaches, but we consider the combination and sequence to be innovative.

The essence of the method involves using the probabilities of various emotions in messages, which are calculated using the Orange software on an external server. Unlike the traditional approach of embedding (i.e., representing text messages in vector form), it is not required here. The embedding may be performed on an external server (this option is referred to as embedding, alongside probability calculation and multi-assessment mode; for more details, see https://orangedatamining.com/widget-catalog/text-mining/tweetprofiler/).

Schematically, we will present the traditional approach and our approach, which will be used as the stages of this research (see Fig. 1). Let's envision testing this hypothesis by carrying out specific steps.

The criterion will be the ability to obtain a result in a binary format – FAKE or REAL. Can the program provide such an answer based on a training dataset and prediction model? We do not claim accuracy in forecasting; we are interested in the possibility of implementing such a straightforward approach, available to almost any computer user.

For this purpose, we will start by forming the training dataset in the first step. This step is no different from the approaches used traditionally by many researchers. In one way or another, we require this foundation for training our neural network. The foundation consists of a repository of fake data available within the software, among many other databases.

While it is possible to involve additional resources with verified fakes, we believe it may not be necessary for our purposes. The program allows for this, but in our view, it won't add significant value. Our objective is to demonstrate the potential application of the proposed approach.

This will provide an idea of the method's simplicity, and its specific effectiveness will depend on the extent to which a particular fake database is tailored to the given purpose.

The database we use does not possess this specificity. We selected it for analyzing Bitcoin-related messages because many fakes are associated with cryptocurrencies. Given the lack of a physical basis for their valuation, they are particularly sensitive to various reports in the media, allowing for speculative profits even from minor price fluctuations.

The fake database, along with other files obtained during the research, is available for download on Google Drive (https://drive.google.com/drive/folders/14CwE5FOHzoXeNL7ZRCbT_HRdQURwEpU6).

RESULTS

In accordance with the schematic representation of the research stages in Figure 1, we have established a workflow within the Orange data mining software (see Figure 2).

This workflow consists of two main "branches." The upper one characterizes the preparation of the training dataset for emotion assessment (without direct embedding) for potential use in prediction.

The lower one contains the formation of the test dataset. We use a corpus of messages from The Guardian news portal for one year (from August 30, 2022, to August 30, 2023) containing the word "bitcoin."

Here's a brief description of the widgets we use:

Corpus Widget: This widget is used for creating a textual corpus from files and sends it to its output channel while maintaining a history of the last opened files. The widget can work with Excel files (.xlsx), value-separated files like CSV (.csv), and its tab-separated files (.tab).

Tweet Profiler Widget: It performs sentiment analysis for each document. The widget uploads data to a server where a model calculates probabilities and/or emotion scores. It supports three emotion classifications, including Ekman, Plutchik (1980), and Profile of Mood States (POMS), Curran, S. L., Andrykowski, M. A., & Studts, J. L. (1995).

Data Table Widget: This widget takes one or more datasets as input and organizes them into an electronic table format. You can sort data based on attribute values and manually select data.

Random Forest Widget: This is an ensemble learning method used for classification, regression, and other tasks. It was first proposed by Tin Kam Ho and further developed by Leo Breiman and Adele Cutler (2001). A random forest builds a set of decision trees. The following widgets will be used in the research process following the proposed methodology:

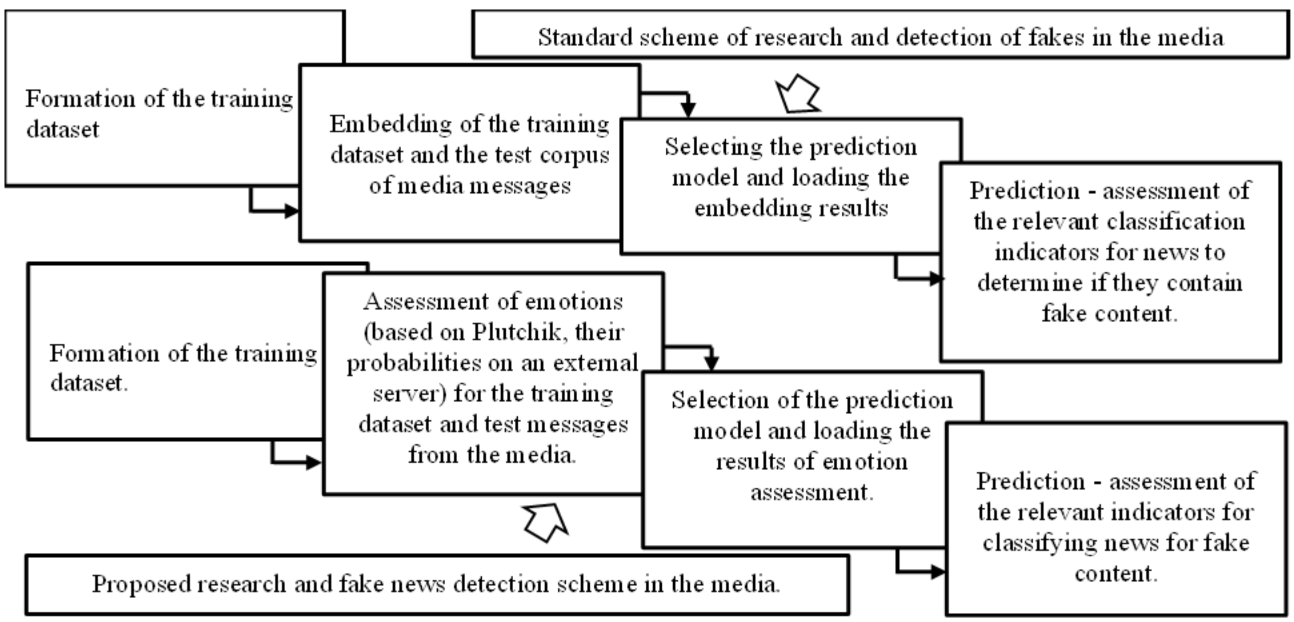

Figure 1. Standard and Proposed Research Schemes for Detecting Fake News in the Media

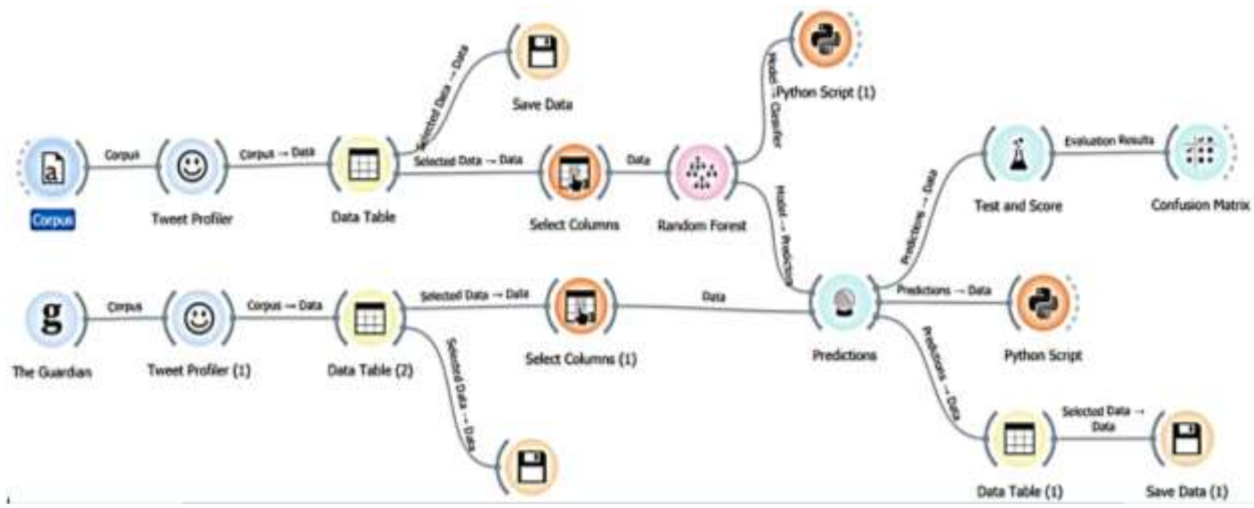

Figure 2: Workflow for Hypothesis Testing

Predictions Widget: This widget takes the training dataset (in our case, the fake-train dataset available in the cloud) and the chosen predictor model (in our case, "Random Forest") as input and provides data and predictions as output.

Save Data Widget: It allows you to save a dataset, provided in the input channel, as a data file with a specified name and in the selected format.

Python Script Widget (Piton Script): This widget is used to run a Python script when the desired functionality is not implemented in an existing widget. After executing the script, variables from the script's local namespace are extracted and used as the widget's output.

Guardian Widget: This widget fetches materials from The Guardian news portal through its API based on specified conditions such as the time period and keywords (e.g., "bitcoin").

Select Columns Widget: It's used for manually forming a data domain.

Test and Score Widget: This widget tests machine learning algorithms. It provides a table with various classifier performance metrics and evaluation results, which can be used by other widgets for classifier performance analysis, such as Confusion Matrix.

Confusion Matrix Widget: This widget displays the count/portion of instances between the predicted and actual class, allowing you to evaluate which specific cases were misclassified and how.

The research process following the proposed methodology will involve sequentially placing these widgets and forming workflows as follows:

Start the "Corpus" widget to load the relevant file with the training dataset (e.g., fake-train from the cloud).

Simultaneously, initiate the "Guardian" widget with specific search conditions for articles published over a defined period (from August 30, 2022, to August 30, 2023) containing the keyword "bitcoin."

Other widgets like "Select Columns," "Random Forest," and "Predictions" can be integrated into the workflow to perform data analysis, predictions, and evaluation of the research process based on the proposed methodology.

The research process involves several steps and the use of various widgets in Orange. The process can be outlined as follows:

Load Data: Use the "Corpus" widget to load the training dataset. Simultaneously, use the "Guardian" widget to fetch articles from The Guardian based on specific criteria (e.g., those containing the keyword "bitcoin" published within the defined timeframe).

Sentiment Analysis: Pass the data from the "Load Data" and "Guardian" widgets to "Tweet Profiler" for sentiment analysis. Two separate "Tweet Profiler" widgets are used, and the condition for this analysis is the Plutchik Multi-label probability for emotional evaluation [21].

Data Evaluation: Continue the flow using the "Data Table" widget for evaluation. This allows you to assess the data collected by the "Sentiment Analysis" widgets, which have emotional ratings. Data is also transferred to "Data Table" (2) for further evaluation. These steps are necessary to save intermediate data and select the information to be passed to the next widget.

Random Forest Model: In the upper flow, use the "Random Forest" widget with standard settings. The results are directly passed to the "Predictions" widget.

Data Selection: In the lower flow, transfer the necessary information from "Select Columns" (1) directly to the "Predictions" widget. The "Predictions" widget output is then passed to "Data Table" (1) to create a table. The results are similar to the data in Table 3.

Table 1: Emotion Assessment (Plutchik's Emotions and Their Probabilities on an External Server) of the Training Dataset, a Fragment of the Table, Fully Available on Google Drive at: https://drive.google.com/drive/folders/14CwE5FOHzoXeNL7ZRCbT_HRdQURwEpU6

Anger	Disgust	Fear	Joy	Sadness	Surprise	Trust	Anticipation	label	text	title
continuous	continuous	continuous	continuous	continuous	continuous	continuous	continuous	FAKE REAL	string	string
								class	meta	meta title=True
2,02E-08	0,00131	8,42E-08	0,881821	0,10394	0,012884	1,85E-06	4,32E-05	FAKE	Tweet Widget by Black Power Front With students joining workers in revolt against South Africa's neoliberal regime, young people a demanding to know why Black police are engaged in the same kind of repression that was previously used by white governments "to systematically counter Black resistance?" In a letter to Black cops, activists note "an increase and worrying pattern of anti-Black police violence." An Open Letter to Black South African …	An Open Letter to Black South African Police Officers

Table 2: Emotion Assessment (Plutchik's Emotions and Their Probabilities on an External Server) of the Test Messages from the Media, a Fragment of the Table, Fully Available on Google Drive at: https://drive.google.com/drive/folders/14CwE5FOHzoXeNL7ZRCbT_HRdQURwEpU6

Anger	Disgust	Fear	Joy	Sadness	Surprise	Section	Headline	Content	Publication Date	Type	…
continuous	continuous	continuous	continuous	continuous	continuous		string	string	time	article	…
						class	meta title=True	meta	meta	meta	meta
4,9922E-07	4,26586E-09	0,00124032	0,99875611	4,0236E-07	2,68436E-06	Technology	Bitcoin is terrible for the environment – can it ever go green?	On the corner of New York's Park Avenue and 52nd Street, curious onlookers recently stopped in front of a giant green skull sitting in the bed of a truck parked outside the office of Fidelity Investments, the global financial management company…	2023-04-26 09:00:03	article	…

Save Data: Save the results using the "Save Data" (1) widget in a format such as Excel for external applications.

Python Script Widgets: Additional widgets "Piton Script" and "Piton Script" (1) are used. Their results are displayed on Figure 4 for those interested in the programmatic components.

Model Evaluation: Finally, assess the effectiveness of the model using the "Test and Score" and "Confusion Matrix" widgets. The results are presented below, specifically in the "Confusion Matrix" section (see Table 4).

The methodology thus involves the sequential use of these widgets and the formation of data flows as described above, ultimately allowing you to evaluate the model's effectiveness.

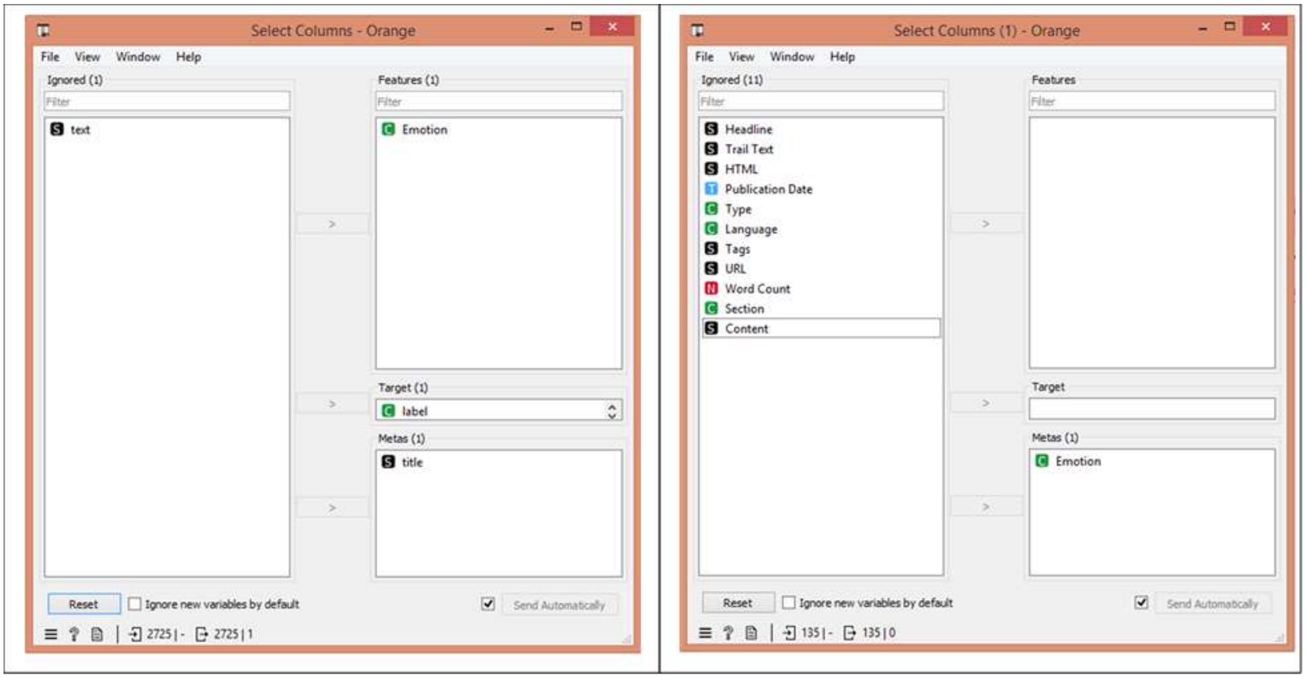

Figure 3: Key Research Conditions in the Operation of the Orange Program (Conditions for the Training Dataset on the Left, Conditions for the Test Dataset on the Right, Top Right - Conditions for Probability Calculation)

Table 3: Assessment of Messages from the Test Corpus (Results of the "Predictions" Widget Based on the Predictive Model "Random Forest," Fragment - The Full Version is Available at https://drive.google.com/drive/folders/14CwE5FOHzoXeNL7ZRCbT_HRdQURwEpU6)

Fear	Joy	Sadness	Surprise	Anger	Word Count	Disgust	Content	Random Forest
continuous	continuous	continuous	continuous	continuous	continuous	continuous	string	FAKE REAL
							meta	meta
0,00124	0,998756	4,02E-07	2,68E-06	4,99E-07	1101	4,27E-09	On the corner of New York's Park Avenue and 52nd Street, curious onlookers recently stopped in front of a giant green skull sitting in the bed of a truck parked outside the office of Fidelity Investments, the global financial management company. The "Skull of Satoshi", named after the pseudonymous bitcoin developer Satoshi Nakamoto, is composed almost entirely of computer circuit boards and fitted with tall smokestacks usually found atop coal power plants. The artifact is a project of artist Benjamin Von Wong and is a reference to the massive amounts of carbon emitted. …	FAKE

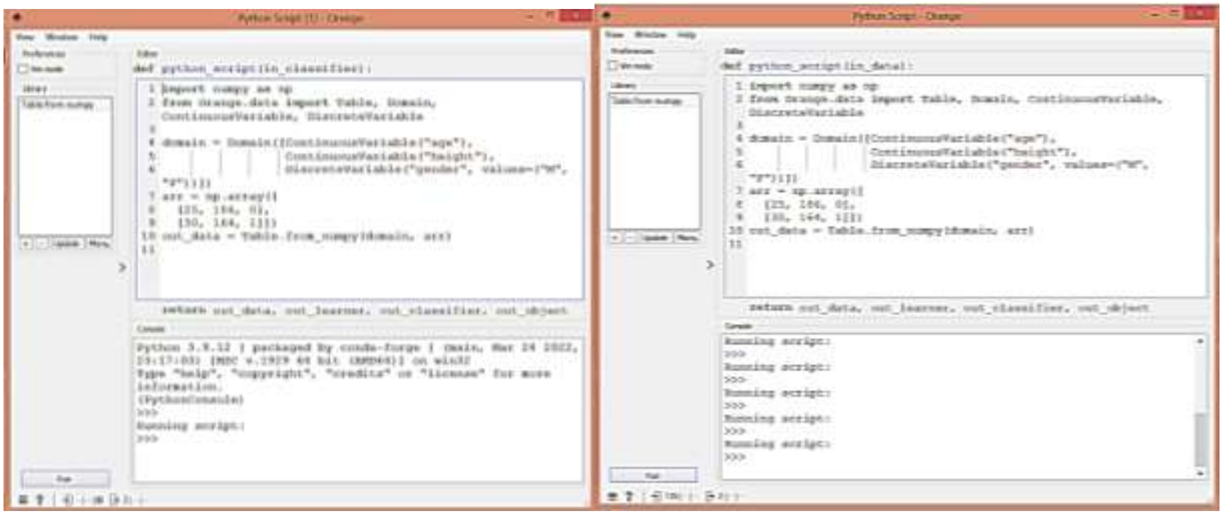

Figure 4. Results of the "Piton Script" and "Piton Script" (1) widgets.

Confusion Matrix

As mentioned earlier, Orange uses a combination of two widgets for model evaluation: Test and Score and Confusion Matrix. The confusion matrix is presented in Table 4: Confusion Matrix

		Predicted		
		FAKE	**REAL**	**∑**
Actual	**FAKE**	85.6 %	14.4 %	**1377**
	REAL	36.8 %	63.2 %	**1348**
	∑	**1674**	**1051**	**2725**

True Positive: The number of fake news correctly identified by the predictive model – 85.6%.

True Negative: The number of real news correctly predicted by the predictive model – 63.2%.

False Positive: The number of fake news that are not actually fake but are classified as fake by the predictive algorithm – 36.8%.

False Negative: The number of real news that are classified as fake by the predictive model – 14.4%.Table 4: Confusion Matrix

Here's the translation of the provided text:

"3- Discussion As a result of the proposed approach, a rather conditional result was obtained for the automatic determination of fake news in media messages. The conditionality of the obtained result is explained by the use of a non-specialized sample, which includes data on fake news detected in financial markets and presented on specialized resources. This goal is not yet a priority. What is of interest is the working principle of the program based on emotional data. In the future, we plan to obtain such databases (which is currently technically challenging) and conduct extensive research not only based on data from The Guardian news portal but also from other publications and resources.

Another direction for improving predictions should be the methodology for forming complex emotions based on the existing assessments. We have already made certain attempts to analyze the concept of irony, in the form of a combination of multiple emotions in messages. Such an attempt was made as part of an RFBR scientific project and aimed at evaluating negative idioms within ostensibly positive statements, which is characteristic of, for example, the Russian language, and not only.

After factor analysis and the reduction of the number of emotions, it may be possible to use other widgets for predictive modeling as alternative options. Currently, they either do not work with multi-ratings or produce unsatisfactory results (e.g., evaluating all messages as fake or only as true).

One of the directions for developing the assessment and detection of fake news based on emotions and other characteristics would be to determine the fakeness rating of a particular publication portal, for example, a fakeness coefficient for both the entire source and individual media messages. This would inform readers about the questionable nature of the content and, to some extent, relieve the news portal or newspaper from responsibility for disseminating such news if the fakeness coefficient exceeded 50 percent. Such coefficients are already presented in some works (for example, our attempt to calculate sentiment coefficients [20]) – we propose to calculate them as follows:"

Please note that some parts of the text contain references to specific projects, methods, and works, which may need further context or information to be fully understood in an academic or research setting.

$$\mathrm{KF}_{\mathrm{article}} = \frac{N_w^h}{N_w^l} \qquad (1)$$

Here's the translation of the provided mathematical expressions and explanations:

"KFarticle – the fakeness coefficient of a news article (essentially its emotional profile); the higher its value, the less trust in the article.

Nwh – the number of words with a high probability of exhibiting specific emotions.

Nwl – the number of words with a low probability of exhibiting specific emotions.

KF_source = N_fn / N_an (2)

KF_source – the fakeness coefficient of a source (media outlet); the higher its value, the less trust in the source.

N_fn – the number of fake news articles in a specific media outlet during a certain period.

N_an – the total number of news articles in a specific media outlet during a given time period (e.g., a year).

In the future, with the development of mathematical tools, we plan to refine these formulas for formalization and use in constructing a working algorithm for assessing the fakeness of news in the media."

These formulas describe the calculation of fakeness coefficients for both individual news articles (KFarticle) and entire media sources (KF_source) based on the number of fake news articles and all news articles in a given period, as well as the presence of words with high and low probabilities of exhibiting specific emotions. The higher the coefficient, the lower the trust in the news article or media source.

CONCLUSIONS

Identifying fakes based on emotions is a rapidly evolving research area, and numerous scientists worldwide are working on this problem. The articles mentioned in this literature review represent only a small part of the existing research, and it is important to continue research in this area to more effectively combat fake information on the internet.

In this research, a relatively simple approach is presented, allowing the assessment of the authenticity of a particular message based on emotion analysis. The approach presented is not new, but our methodology stands out for its ease of use, transparency throughout the entire process, and it does not require deep programming knowledge from the researcher. The conducted research can easily be replicated on various scales since the Orange software is open-source, easy to install, and does not demand significant computer hardware resources. The most extensive calculations (e.g., determining emotion probabilities, as in our case) are carried out on an external server. The Orange widgets used in our approach enable the efficient and rapid formation of the entire fake identification process. In case of any errors, the widget will not function and will provide the cause of the failure, allowing for quick rectification.

Applying our approach resulted in fake/real ratings that mostly aligned with false/true messages. We determined the accuracy percentage using the tools available in the program. However, we consider it somewhat inaccurate to present them because the training dataset was not specifically designed for assessing Bitcoin-related messages (political topics and COVID-19 were excluded for ethical reasons, and Bitcoin was the third most common subject for fake messages).

In conclusion, we present two formulae for assessing the authenticity of messages in the media and the source as a discussion topic. These formulae undoubtedly require refinement, and perhaps some researchers have been using them in some form or another. We don't claim exclusivity or authorship but have simply attempted to explain how our approach can be practically applied.

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