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RESEARCH ARTICLE

Detection of Financial and Political Fake News As a Measure to Prevent Instability in Financial Markets

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This article explores the role of social networks as a catalyst for instability in financial markets. Its purpose is to present strategies for mitigating the media's influence on adverse outcomes, primarily by analyzing the information cascades and related transactions in stock markets. The innovative aspect of this research lies in the development of methods for analyzing specific types of information, particularly media reports, to identify indicators of fake that distort public perception. The focus of this study is on fake news and the analysis of its potential linguistic features for identification purposes. A significant outcome of this research is the establishment of a comprehensive method for conducting preliminary linguistic analysis of text content from economic and political news portals, enabling a reliable assessment of information credibility. I propose a methodology that acts as a preventive tool—a proactive measure to mitigate the impact of social media posts on the financial sector. The correlation between identified fake news and stock market dynamics is 0.5, indicating a noteworthy relationship. Additionally, predictive models were tested, and neural networks proved to be the most effective.

Keywords: instability, social networks, stock exchange, information fake, linguistic analysis

This study explores various aspects of financial and political information sources, particularly social networks, focusing on their impact on financial markets as independent triggers of financial instability. Such instability often arises in response to the panic incited by online messages. This wave of panic can create a cascading effect, leading to substantial financial transactions executed within remarkably short time frames, often during a single trading session or day.

The absence of mechanisms to manage reactions and curtail impulsive behavior among financial market participants highlights the need for protocols that encompass multiple facets of social science methodology. This includes components of crisis economics, trading psychology, big data informatics, and technical considerations related to the implementation of new methods within trading platform systems. These platforms are closely connected to specialized thematic chat forums and blogs tailored for market participants, functioning effectively as social networks of varying scales

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Description of the Research Methodology and its Justification

The research methodology is divided into three large blocks:

1. Analysis of financial news and its impact on the stock market, especially in relation to investor psychology;

2. Detecting fake news using linguistic features; for this purpose, I plan to develop my own training dataset using text mining tools, including emotion analysis based on the Plutchik (1980) model; and

3. Study the impact of fake news on trading volume and stock profitability. Standard statistical methods will be used to assess the correlation between emotional reactions and market fluctuations.

The psychological foundations of social media's influence on the stock market can largely be traced to the herd instinct. Indeed, market movements are often more a product of psychology than of mathematics. As Keynes (2012) noted, the roots of economic crises and market panics frequently stem from this herd mentality. This concept is particularly relevant when examining the inflation of financial bubbles and the role of the "leader of the herd." Typically, this leader is an elite figure—a successful individual seeking to amass as much wealth as possible. In turn, this attracts a "herd" of individuals who emulate the actions of others and follow the leader's opinions. Many aspiring investors attempt to replicate the leader's success by mirroring their trades, often relying solely on these traders' insights, which can lead to significant losses.

In financial markets, this phenomenon is characterized by a cascading effect that heightens agents' expectations, ultimately increasing market volatility. In this context, traders aim to maximize their profits through social media, potentially manipulating the market by luring in other investors swayed by their actions.

Investors should base their decisions on their own thorough analysis rather than merely following popular opinion. A new subtype of crisis has emerged—one that is particularly dynamic and can be artificially and subjectively triggered through the dissemination of information by influential market figures, often referred to as gurus, or by groups colluding with vested interests.

The widespread adoption of social networks as the primary medium and mobile banking applications has enabled customers to transfer substantial amounts of money with just a few taps on their devices. Financial market experts who examine these trends note that this shift has altered the dynamics of mass withdrawals driven by customer concerns about the stability of their banks. Although social media sentiment can significantly influence market dynamics, experts caution against overestimating its effects. Information shared on social networks may be incomplete, inaccurate, or outdated, and messages may be manipulated for ulterior motives, including the spread of fakes. Therefore, it is vital to use social media data as just one of several factors in market analysis, alongside more traditional and reliable sources of information.

Social media has emerged as the predominant force among various media tools, serving as effective channel for attracting investors, sharing information, and discussing trends in financial markets. However, these platforms also pose risks by facilitating the spread of fakes and influencing public behavior. Although not every social media post can incite instability in local financial markets, instances such as the GameStop phenomenon demonstrate how social media investors have shown a steadfast commitment to purchasing and holding stocks, often using internet memes to foster enthusiasm on platforms like Reddit, Twitter, and YouTube.

The issue of fake news distribution was examined by Soroush, Roy, and Sinan (2018). Their research delves into the dynamics of how true and false news circulate in online environments, providing valuable insights into the nature of fake news dissemination on social media platforms.

Automated methods for detecting fake news have largely been developed overseas. A recent study by Thorne and Vlachos (2018) introduced automated fact-checking techniques and highlights various dimensions of this process. Additionally, Shu et al. (2017) explored the challenges of identifying fake news on social networks through data analysis. These approaches predominantly employ machine learning and data analysis methods to classify false information based on its structural characteristics and distribution patterns within social networks.

One of the most noteworthy methodological advancements has been achieved by an international team comprising researchers (Clark et al., 2019) from institutions in the United States and Hong Kong. Their access to extensive databases enabled them to draw several significant conclusions:

– Fake news articles receive an average of 83.4% more page views than legitimate news articles and are retweeted 70% more frequently.

- On the day fake news is published, there is a noticeable increase in trading volume, although this is still lower when compared to genuine articles.
- Editors opt for fake news 8.1% less often.
- Statistically significant differences were identified in 65 of the 93 output variables related to language expressions, indicating a high likelihood of deception.
- Linguistic features may also serve as indicators of deception by managers during telephone and video conferencing.

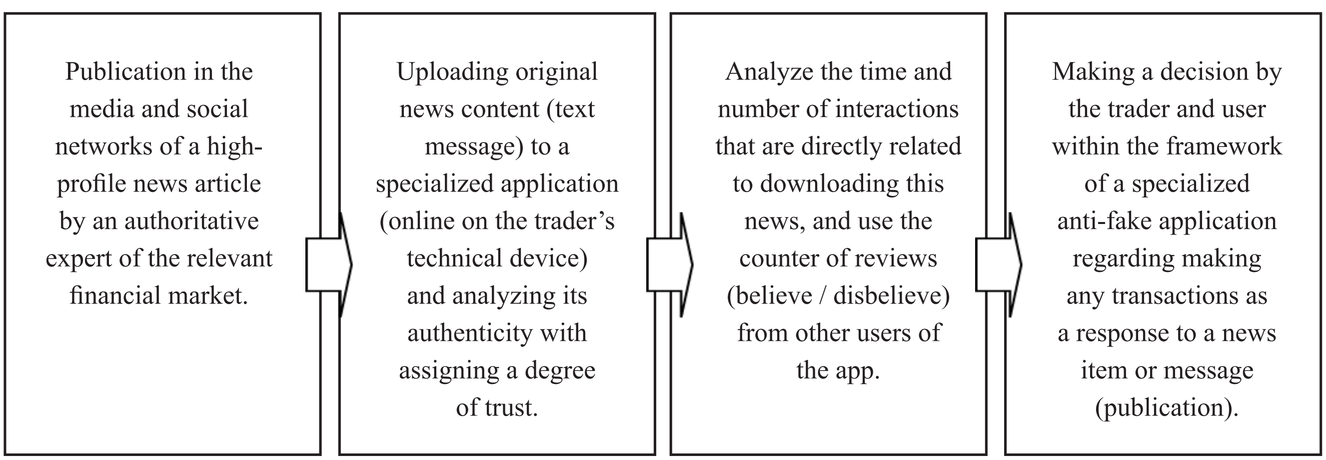
Clark et al. (2019) also note a decline in detection of fake content after the Securities and Exchange Commission cracked down on stock promotion schemes in the region in 2017.

To differentiate the approach outlined in this article from that of the previously mentioned authors, it is essential to elaborate on their information processing structure. The discussion is organized into three sections: (a) the impact of fake news on investors' attention; (b) methods for identifying fake news using linguistic features; and (c) the effect of fake news on trading volume and stock dynamics. Given the complexities involved in gathering information for the average trader—particularly in points (a) and (c), where both analysis and the selection of appropriate instruments demand significant time—this article primarily focuses on point (b), based on its ranking. The methodology employed in this study closely mirrors that of the international consortium of researchers, who utilize six established classification algorithms: gradient boosting, logistic regression, naive Bayes, neural networks, random forest, and support vector machines. These algorithms are applied using 93 output variables from the LIWC 2015 software package, with the Scikit-learn package in Python facilitating training and testing.

The influence of news and media reports has been the subject of various studies, with several notable articles highlighting different facets of this topic. One such article concentrated on the effects of political events on stock market dynamics and provided valuable methodological insights (Rus et al., 2022). The authors underscored various approaches to information retrieval, including event analysis and validation methods to counter disinformation.

Another publication addresses the manipulation of dividend payments to sway stock prices (Franklin & Rodiel, 2021). Although the authors touch upon this issue, they did not explore it in depth; notably, insider trading lies outside the scope of their analysis.

Additionally, a follow-up study investigates the relationship between the real and financial sectors (Prukumpai, 2019), a crucial aspect for understanding how the stock market reacts to specific events, particularly when information originates from government and fiscal authorities but has yet to reach



Source: Developed by author

Figure 1
Sequence of Actions of a Financial Market Participant (Trader) When Breaking News of an Economic and Political Nature Appears in the Form of Messages in Social Networks From *Reputable Market Experts*

broader market participants. Although this work is systematic in nature, it does not cover the narrower topics of insider trading or the potential manipulation of such critical information.

The management of a standard trader message is illustrated by the sequence presented in Figure 1.

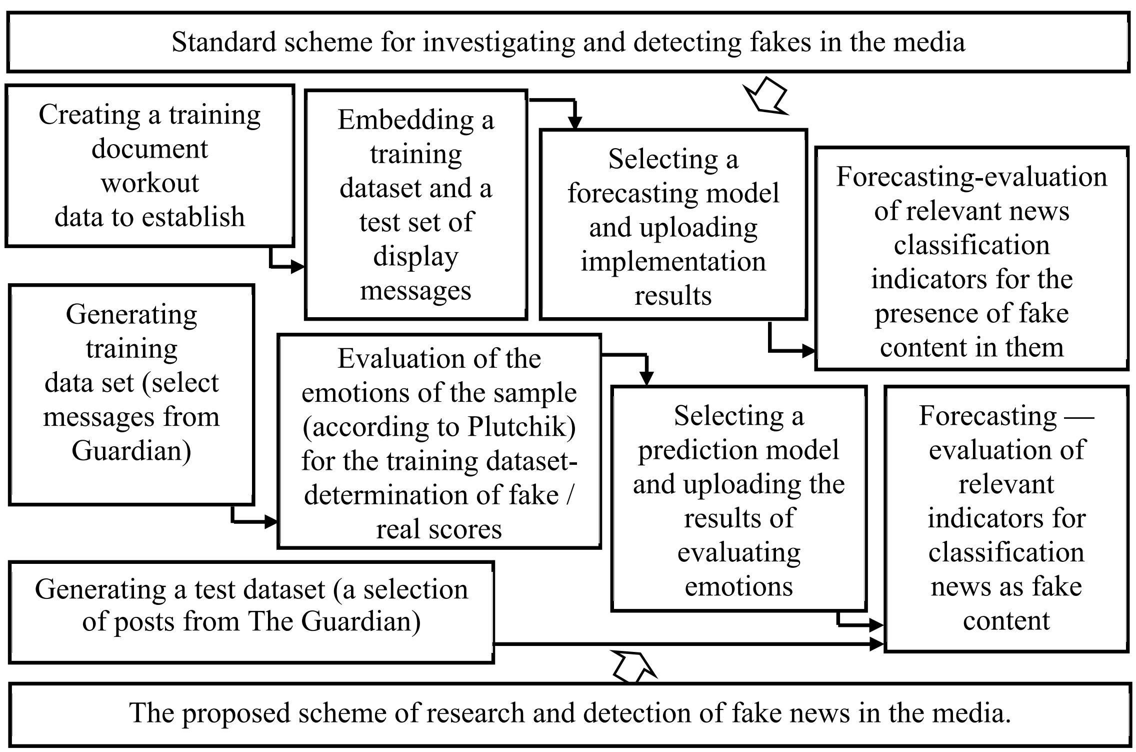
As illustrated in the diagram, the primary methodological objective of my future research is to develop a tool for to assess the truthfulness or falsehood of specific internet messages on the internet. A number of researchers have explored methods for detecting fake news based on linguistic characteristics, (Malyshenko et al., 2024). I aim to leverage my best practices to tackle this issue by examining unique facets of the current research landscape. To accomplish this, I plan to create an original training database utilizing text mining tools, specifically through emotion analysis grounded in Plutchik's (1980) model.

This method entails calculating the probabilities of various emotions present in messages using Orange software on an external server. To clarify, I outline the distinctions between the traditional approach and my proposed methodology, as detailed in the steps of this study (see Figure 2).

Research Results

The methodology employed in this study presents a distinctive approach to addressing challenges faced by international researchers working with linguistic information derived from text messages.

For data processing, I utilized the "Orange" software tool, which features a "Text Processing" function available as a widget. The entire data processing workflow is visually represented as a sequence of interconnected widgets, with sentiment analysis as the central component. I tested the following hypothesis: all instances of fake news contain common linguistic expressions that can be partially identified. To pursue this objective, I developed a training dataset based on an author's database of fake news classified through emotion analysis (Malyshenko et al., 2024). I then



The goal is to get the result in the FAKE / REAL format.

Figure 2
Standard and Proposed Research Schemes for Detecting Fake News in the Media
[based on Malyshenko, Malyshenko, & Mardar, 2024]

applied real data from an economic news database, which included instances of fake news not present in the training dataset. This approach enabled me to evaluate the performance of several widely used forecasting models and the effectiveness of fake news detection. It is important to note that this evaluation was conducted on a preliminary basis, without ranking the accuracy of identification (i.e., the extent to which it correctly identifies fake news).

The Orange database was utilized in a modified form as a training database. For the test database, I selected a biased sample from the Guardian news publication, specifically targeting economic and political news from a defined time period that included the term “Putin.”

The study will unfold in several stages:

1. Creation of a training database based on emotional assessments.
2. Use of this database as a foundation for evaluating the new test database.
3. Assessment of the correlation between the generated probability estimates (fake/real) and indicators of stock market dynamics.
4. Comparison of our methodology with that proposed by the developers of Orange, referencing the work of Demsar et al. (2013).

In the initial phase (**Step 1**), I compiled a training dataset utilizing sources such as The Guardian. Although I can expand the list of sources, it is essential to clarify that this study does not prioritize socio-political aspects; therefore, I cannot assert that it will be fully representative. My primary objective is to demonstrate the capability to identify fakes based on emotional content. Orange allows for the inclusion of the New York Times, in addition to the Guardian, and other media outlets may also be utilized. However, it is important to note that many leading publications often repeat reports disseminated by government agencies, such as the U.S. State Department.

The training database is composed of a collection of messages covering the specified period. To enhance the effectiveness of fake detection, I employed the keyword “Putin.” Although this approach may seem somewhat unconventional, practical experience has demonstrated its efficacy; however, I do not claim its universal applicability.

The fake database, along with other files generated during the research, will be made available for download on Google Drive (https://drive.google.com/drive/folders/1pOnhyNC-m2i3xMlVtLNVA8D36xaWUzNF?usp=sharing).

The workflow for creating a training database is shown in Figure 3.

I curated a selection of news from The Guardian covering the period from August 21, 2023, to August 21, 2024. To achieve this, I utilized “The Guardian” widget, which enabled me to collect a total of 2,432 messages. Once data were gathered, I implemented the selection using the Document Embed widget and calculate the distances between rows or columns in our database using the Distances widget. Subsequently, I identified clusters, with a particular focus on the three largest ones: the first cluster is expected to contain the most emotionally charged content (potentially including misleading information), the second will comprise messages with a moderate emotional tone

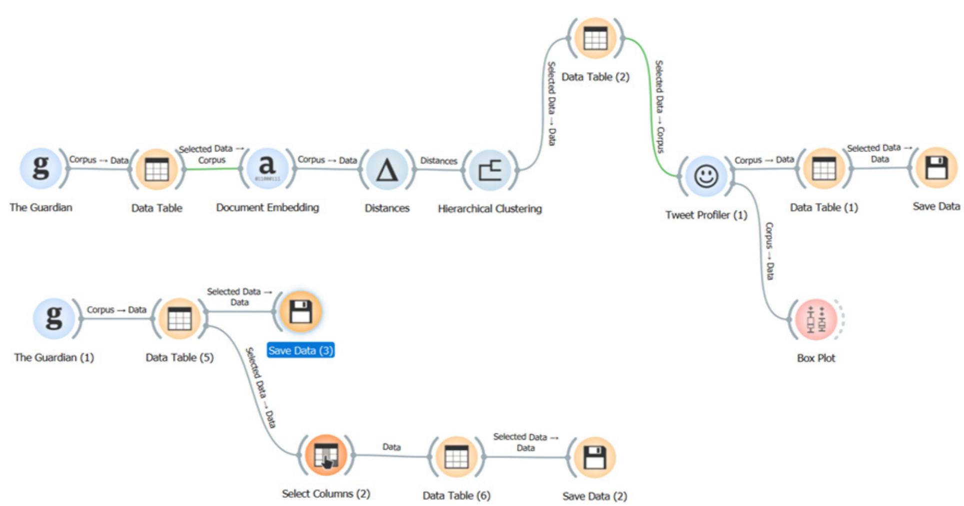


Figure 3
Workflow for Creating a Learning Base in Orange

(routine updates that express low emotion but are factual), and the third will consist of messages with minimal emotional content—those that are anticipated, planned, and contain truthful information. Please refer to Figure 4 for a fragment of the Hierarchical Clustering widget.

After the clusters were selected, I performed an emotional assessment of the sample based on the companion model. The Tweet Profiler widget extracts mood-related information from the server for the document and sends this data to the server, where the model calculates probabilities for various emotions

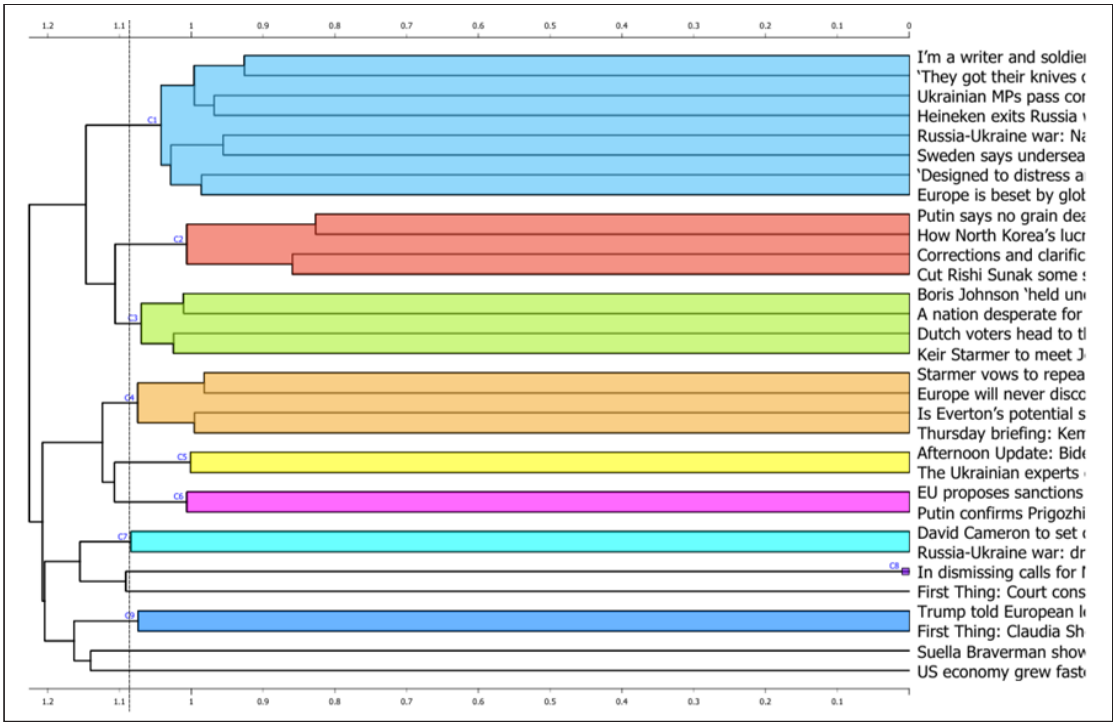


Figure 4
Cluster Analysis of the Sample

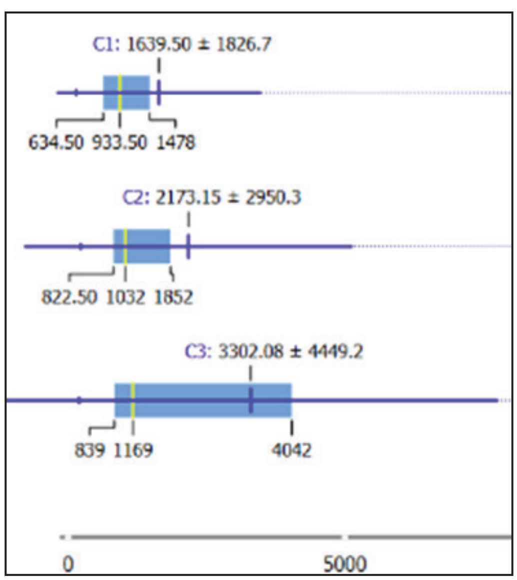


Figure 5
Number of Words by Cluster (Rectangular Chart Widget, the Fields Display the Final Values, the Average, and the Median)

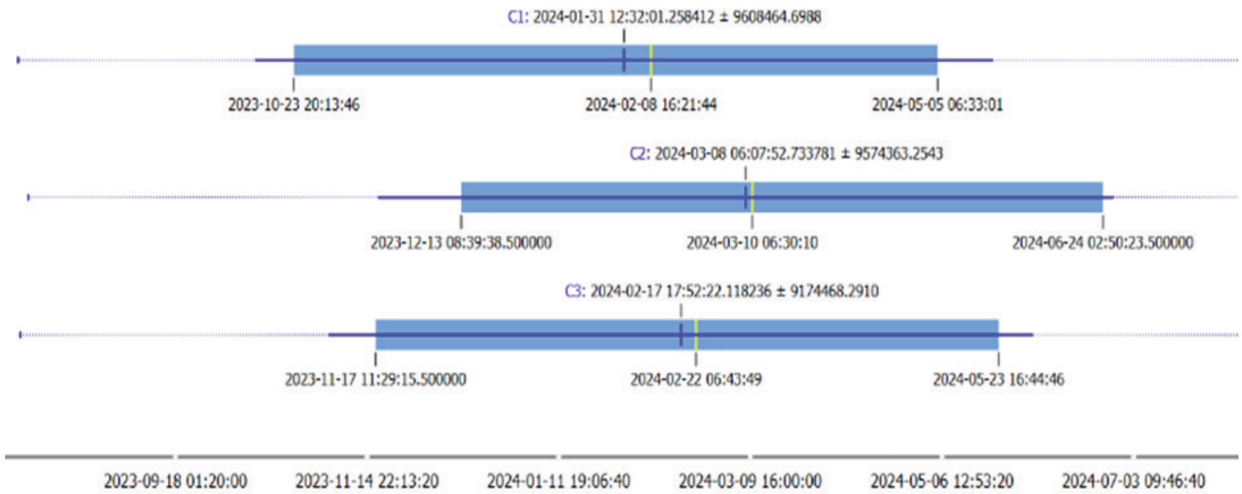


Figure 6
Number of Publications by Date, Broken Down by Cluster (Rectangular Chart Widget, the Fields Display the Final Values, the Average, and the Median)

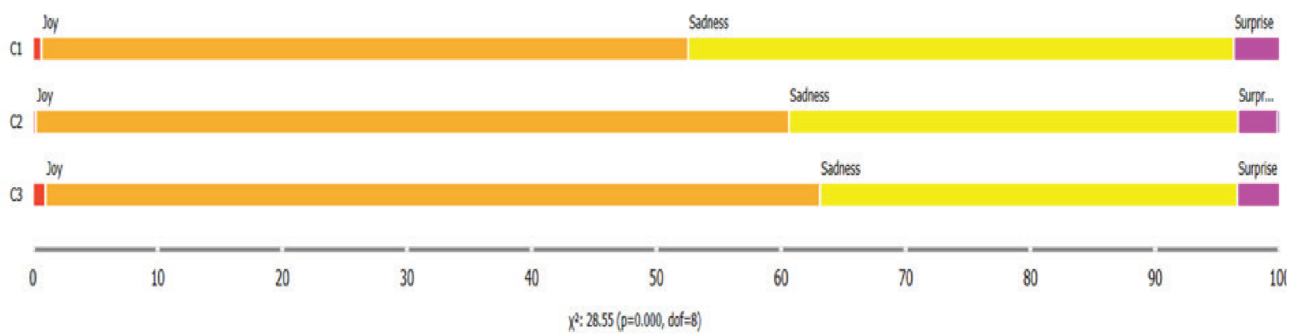


Figure 7
Distribution of Probability Estimates of Evolution Across Clusters as a Whole

or ratings according to the Plutchik framework. The resulting clusters can be described as:

1. The number of words in each cluster is shown in Figure 5:

2. The number of publications by date is shown in Figure 6.

   The graphs indicate that the first cluster has the fewest words; nevertheless, the distribution of messages by date remains relatively consistent. Specifically, the first cluster comprises 1,486 messages, whereas the second has 447 and the third contains 499. Interestingly, the first cluster displays an anomaly, featuring significantly fewer words but generating two and a half times more messages compared to the second and third clusters.

7. I also analyze the emotional component of messages by cluster (see Figure 7).

   As shown in Figure 7, the difference between clusters is minimal. For a more detailed analysis, I looked at how emotions are distributed across clusters, as shown in Figure 8.

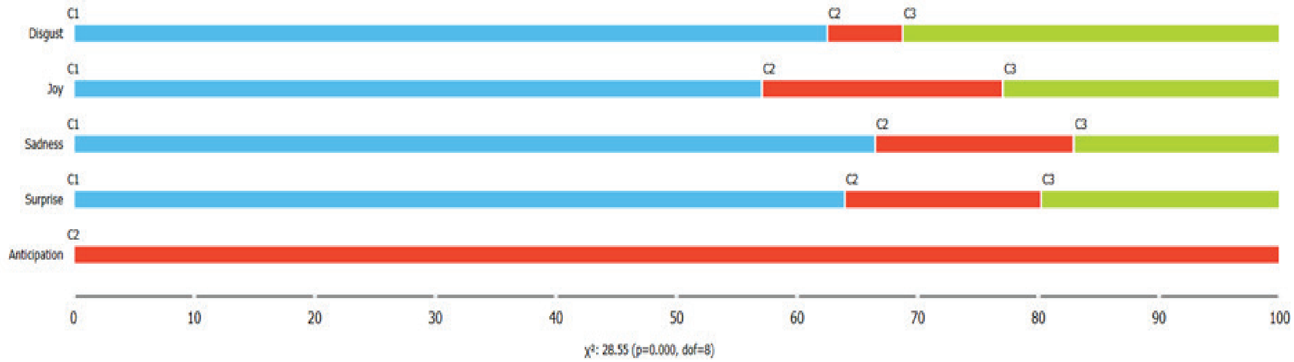


Figure 8
Distribution of Emotions Across Clusters

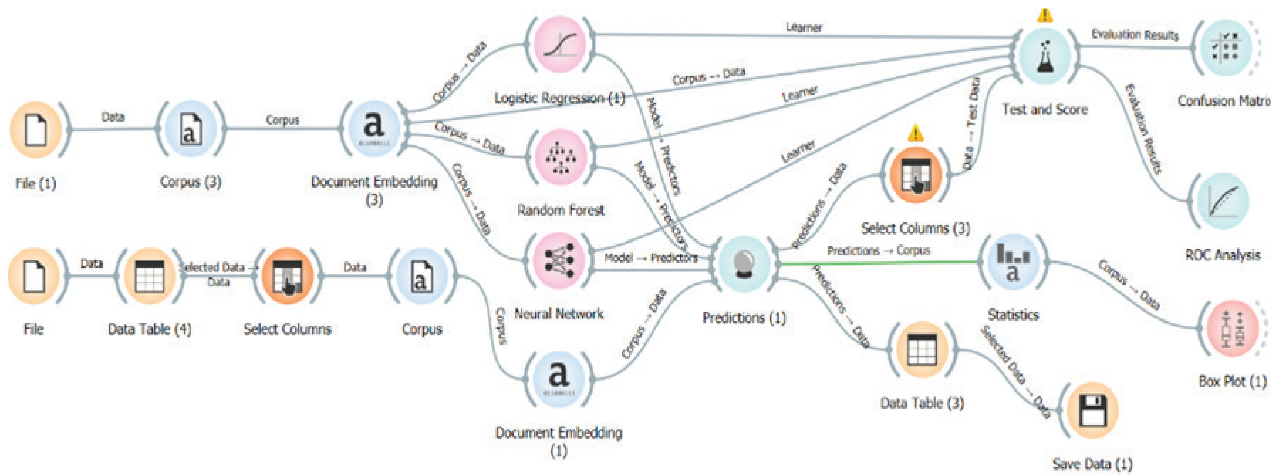


Figure 9
Workflow and No Testing Software Sample in Orange

Based on the observed distribution of emotions across the clusters, the first cluster stands out as the most emotionally charged. I recommend using this cluster as a training sample. Although this approach simplifies the process, additional details on selecting a fake cluster based on emotional criteria can be found in Malyshenkoet al., 2024). Next, I created a test sample, depicted at the bottom of the figure, which spans the period from August 22, 2024, to September 22, 2024, and encompasses 166 messages.

Step 2. At this stage, having identified cluster number 1 as fake, I classified the messages from this cluster as FAKE, while labeling messages from the other two clusters as REAL. This classification is more conveniently executed in Excel. The outcome becomes the new file that I utilized as training dataset (fake-TRAIN_MOYA_2_ASSESSMENTS_MOYA_2_ASSESSMENTS).

The new workflow in which I used the database as a learning tool is shown in Figure 9.

The models chosen for this analysis include "Ra& DForest," "Logistic Regression," and "Neural Network." The database scores are notably high, largely due to the intentional inclusion of fakes in the sample, particularly given the keyword "Putin." Furthermore, the data set utilized for training and subsequent testing somewhat skews the results. For additional details, please refer to Table 1.

Thus, I additionally calculated the "confusion matrix," which shows the proportions between the predicted and actual class (read more at https://orangedatamining.com/widget-catalog/evaluate/confusionmatrix://orangedatamining. com/widget-catalog/evaluate/confusionmatrix/), as shown in Table 2.

As can be seen from Table 2, the most effective method is neuralnetwork.

After applying the training sample of 2,432 messages to a new test sample of 166 messages, as illustrated in Figure 8 (lower workflow), it is observed that the estimates for the frequency of received documents did not vary significantly: 95 were classified as fake, and 71 were categorized as real. Given the limited sample size (only 166 posts for the analyzed period) and the generally accepted constraints (one keyword, one source), these results were entirely anticipated. I organized the findings using the "FAKE / REAL" scoring system, which, following a minor recoding (FAKE – 1; REAL – 0), is presented in Table 3.

Table 1. *Test and Evaluation (Testing of Used Forecasting Models)*

(None, show average over classes)						
Model	**AUC**	**CA**	**F1**	**Prec**	**Recall**	**MCC**
Logistic Regression	0,977	0,923	0,923	0,923	0,923	0,838
Random Forest	1,000	0,990	0,990	0,990	0,990	0,979
Neural Network	1,000	1,000	1,000	1,000	1,000	1,000

Table 2. *Confusion Matrix (Testing of Used Forecasting Models Based on the Author's Database Containing 2,432 Messages)*

Model / Mark	Logistic Regression			Random Forest			Neural Network		
	FAKE	**REAL**	**Σ**	**FAKE**	**REAL**	**Σ**	**FAKE**	**REAL**	**Σ**
FAKE	1404	82	**1486**	1477	9	1486	1486	0	1486
REAL	105	841	**946**	**15**	**931**	**946**	**0**	**946**	**946**
Σ	1509	923	2432	1492	940	2432	1486	946	2432

Table 3. *Fragment of the Test Sample Evaluation Result Based on the Author's Training Base (Fragment)*

Publication Date	**Headline**	**Random Forest**	**Logistic Regression**	**Neural Network**
time	string	FAKE - 1; REAL - 0		
meta	meta title=True	meta	meta	meta
2024-08-22	Ukraine strikes airfield near Volgograd as Russia presses forward in Donetsk	1,00	1,00	1,00
2024-08-22	Tim Walz rallies Democrats in biggest speech of his life – as it happened	0,00	0,00	0,00
…	…	…	…	…
2024-08-24	Let us show Putin we have ability to hit targets deep inside Russia, Ukraine urges west	1,00	1,00	1,00

Initially, I set the count of true reports to zero. Although this may appear unwarranted at first glance, a thorough analysis of real news indicates that such messages are typically anticipated, spread rapidly, and often reflected in market quotes a few days prior to their official announcements. These reports are usually planned and generally lack significance for the market, as they do not signify substantial profit opportunities—except in the case of rare global disasters or the onset of wars. Market prices tend to increase gradually; however, the most compelling scenario for speculators is to see prices decline, allowing them to purchase at a lower rate and then sell at a higher price once exchange rates stabilize.

Moving forward, I consolidated the estimates by date (as shown in Table 4). This enabled the exclusion of text data, which is a sensible approach. Doing so allows the efficient accumulation of probabilities and help mitigate issues associated with clustering, particularly the duplication of different events occurring within the same timeframe.

Step 3. In the next step, I checked the correlation between the estimates obtained and the London Stock Exchange quotes for the same time period. As you may know, the exchange does not work every day - accordingly, those dates that fell on the weekend were also removed from the table. The result is shown in Table 5.

Following the correlation analysis presented in the Excel table, it was observed that daily turnover exhibited the most significant correlation. According to my evaluation, the neural network model proved to be the most effective, demonstrating a correlation of approximately 0,500 (0.488), which is regarded as a notable correlation. Please refer to Table 6 for further

Table 4. *Probabilistic Estimates of the Tested Sample Based on the Author's Training Base (Obtained by Adding False Probabilities for a Certain Date, Fragment)*

Publication Date	Model		
	Random Forest	Logistic Regression	Neural Network
20.09.2024	5,00	4,00	4,00
19.09.2024	4,00	4,00	4,00
18.09.2024	2,00	2,00	2,00
…	…	…	…
22.08.2024	1,00	1,00	1,00

Table 5. *Data on the London Stock Exchange Quotes for the Corresponding Dates of the Studied News From the Test Sample (Fragment)*

Date	Price open	Price min	Price max	Price ast	Turnover	Number of transactions
https://www.londonstockexchange.com/						
22.08.2024	9984,00	9984,00	10050,00	10010,00	8439 525 324	3365
23.08.2024	10050,00	10010,00	10075,00	10010,00	7021 318 306	2703
…	…	…	…	…	…	…
20.09.2024	10260,00	10225,00	10380,00	10315,00	21843 661 018	4729

Table 6. *Correlation of Probabilistic Estimates of Messages for Various Models With the Dynamics of the Stock Exchange (Daily Transaction Volume)*

CORRELATION (model/turnover)		
Random Forest	**Logistic Regression**	**Neural Network**
0,408085469	0,447238821	0,487456047

details.

This correlation, considering all previously accepted constraints, yields a relatively high result and can be deemed quite satisfactory. In Malyshenko, Malyshenko, & Anaskina (2018), the correlation between events and stock price dynamics were assessed. However, the relationship between fakes and trading volumes was particularly notable, especially when one takes into account the information efficiency of the stock market. This efficiency reaches only a weak form, as noted by Y. Fama (1970), primarily in developed markets, and even then, it is not consistent across all time periods, given the persistence of various anomalies.

Step 4. I carried out a comparative study utilizing the database provided as an example on the Orange developer site (fake-train.tab), as illustrated in Figure 10.

Analysis and Explanation of the Results

The developer training database, known as Orange, offers a distinct advantage because it comprises a collection of messages that have undergone rigorous

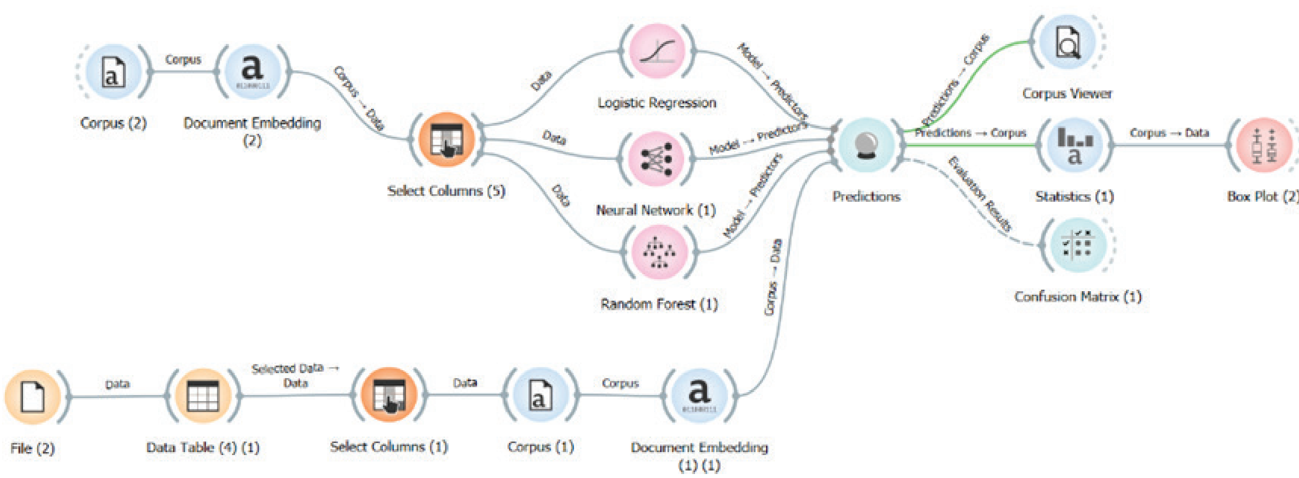


Figure 10
Example of an Orange Testing Workflow

Table 7. *Frequency Analysis Using the Database From the Orange Example*

	Random Forest	**Logistic Regression**	**Neural Network**
FAKE	115	138	129
REAL	51	28	37

screening to ensure that each one is fabricated. This database is meticulously organized and showcases a variety of examples that are particularly illustrative. The messages included are not only thoughtfully selected but also form part of an “advanced” testing database, where each message is chosen for its relevance and quality. When I employed the same predictive models to assess my own test base, using this database as a benchmark, I achieved the following impressive results, as shown in Table 7

The data presented in Table 7 shows that in this iteration the number of detected fakes ranged from 115 to 138, which is slightly higher than my maximum of 96 cases. Although the potential accuracy of their methodology appears to be higher, a comprehensive analysis reveals a significant limitation: it fails to account for the source of messages included in the training sample. This limitation persists despite the fact that the volume of signals, in terms of speed, aligns closely with my dataset—2,432 messages in the collection compared to 2,725 in the Orange dataset.

Even if I concede that their prediction accuracy is superior, which could theoretically enhance performance, the standard analytical approach necessitates a robust training database. This database must be continually updated to adapt to the swiftly changing socio-political landscape; otherwise, its reliability may diminish over time. I contend that maintaining such an up-to-date training database will require substantial time and manual effort. Given the rapid fluctuations typical of stock markets, this may render the approach impractical.

The methodology presented in this study demonstrates notable effectiveness, although it does not yield completely accurate results. This limitation can primarily be attributed to the relatively small size of the training database, which could be expanded if not for the technical constraints I faced. It is essential to highlight that the objective was not to identify the model with the highest accuracy, as the sample was inherently limited to a keyword that formed the overarching theme of all analyzed messages. A significant advantage of the methodology discussed is its user-friendliness, making it accessible even to individuals without programming experience. This democratization of technology allows users to navigate complex information systems and coding methods with ease. The Orange platform further enhances this experience by enabling users to create custom scripts tailored to their specific needs. Overall, the product is designed to be intuitive, visually straightforward, and equipped with a diverse range of tools, making it easy to use for a broad audience.

Conclusion

The financial market, recognized as the most modern and dynamic sector of market relations, is experiencing significant and active transformations. This evolution is primarily driven by the rapid advancement of digital technologies and the increasing importance of social and informational institutions. Research in the stock market transcends mere financial and transactional interactions; it delves deeply into the psychological intricacies of trading and the behavioral patterns exhibited by large social groups. All processes within this research domain, along with the resultant phenomena—such as the unintended consequences of social media, the influence of key opinion leaders and social influencers, the rise of financial bubbles, sudden surges in trading volumes, and erratic price fluctuations—can be strategically harnessed. These occurrences present opportunities for both unscrupulous actors and well-meaning advocates who strive to promote universal access to information. It is essential to acknowledge that social networks have evolved into not only dependable channels for communication and information dissemination but also complex tools capable of manipulating the subtleties of the financial market. This duality underscores the intricate interplay between technology, psychology, and market dynamics in today’s financial landscape.

Acknowledgments

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