Exploring the potential of e-learning in economic crisis prediction

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Abstract: *This study explores e-learning's potential to anticipate economic crises, positioning it as a key tool for global financial stability. By leveraging AI-driven text analysis — proven effective in financial forecasting — five predictive algorithms were assessed: exchange rate processing, logistic regression, linear regression, recurrent neural networks, and sentiment analysis. Using a 2008–2018 dataset, the goal is to develop an e-learning system that delivers reliable crisis predictions, enhancing proactive economic risk management.*

Keywords: e-learning, AI, economic crisis, predictive models, financial forecasting.

1. Introduction

This paper discusses the use of natural language processing (NLP) in e-learning, particularly for anticipating economic crises by analyzing public discourse. NLP has advanced to the point of "understanding" human language (Gîfu & Trandabăț, 2023; Alhawiti, 2014) and handling complex tasks such as stock price forecasting (Chelmuș *et al.*, 2018; Gîfu, 2020) and financial sentiment analysis (Li & Shah, 2017).

The study hypothesizes that public discourse, which reflects crises like political ones (Gîfu & Cristea, 2012), can be characterized through sentiment analysis (Gîfu & Cioca, 2014a/b; Delmonte et al., 2012/2013) based on economic crisis triggers. To test this hypothesis, five deep learning algorithms (detailed later) were applied, focusing on the 2007 U.S. financial crisis, which quickly became a global downturn with recessions and credit collapse (Bach et al., 2019; Hsu et al., 2018). An economic crisis generally indicates a state's inefficient economic management (Gîfu, 2015).

This research addresses a fundamental question: Can e-Learning and Public Discourse Analysis Prevent Economic Crises?

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To answer this, the RoMarketPulse tool was developed — an advanced NLP and machine learning application trained on an extensive corpus of economic news articles. This tool aims to predict imminent economic crises, starting with the 2008 global financial collapse, when major U.S. banks and financial institutions failed, by identifying early warning signals of financial instability.

The paper is structured as follows: Section 2 reviews existing approaches to economic crisis prediction. Section 3, the core of this study, details the proposed system, focusing on the dataset and deep learning methodology used to forecast global economic crises. Section 4 presents an analysis of the results and system performance, followed by concluding remarks in the final section.

2. Background

Before the 1980s, discriminant analysis was the primary method for bankruptcy prediction, later improved by combining it with logistic regression, achieving over 90% accuracy (Arora & Ravi, 2013; Svaboda et al., 2020). Currently, logistic regression remains widely used for assessing financial distress probability (Xiao et al., 2012; Li et al., 2017; Oz & Yelkenci, 2017; Ashraf et al., 2019), although the increasing nonlinearity of financial data (Ecer, 2013) has spurred the adoption of more sophisticated approaches. Backpropagation Neural Networks (BPNs) have been employed for bankruptcy risk classification (Aydin & Çavdar, 2015) and, in conjunction with discriminant analysis, for early economic crisis warning signals (Wang & Wu, 2017). In Romania, crisis analysis relied on semantic text classification until 2015 (Gîfu & Cristea, 2012).

Since the 1990s, Machine Learning (ML) and Deep Learning (DL) have become dominant forces in economic crisis forecasting, encompassing techniques like decision trees, hybrid classifiers, and ensemble models. Beyond these, the rapid evolution of DL has introduced powerful new architectures. Recurrent Neural Networks (RNNs), particularly those using character-level linguistic models, have demonstrated strong performance in stock market prediction (Pinheiro & Dras, 2017), showcasing the value of sequential data analysis.

However, more recent advancements in deep learning offer even greater potential. Transformer-based models, such as BERT (Devlin et al., 2018) and its successors, are now being explored for their ability to capture complex contextual relationships in financial text data, including news sentiment and expert commentary. Furthermore, the emergence of Large Language Models (LLMs) like GPT-3 (Brown et al., 2020) and LaMDA (Thoppilan et al., 2022) open new avenues for analyzing economic discourse at an unprecedented scale and understanding nuanced market sentiment. Even more cutting-edge approaches, like Quantum Natural Language Processing (QNLP), while still nascent, hold the promise of revolutionizing financial text analysis (Stein et al., 2023) through the power of quantum computing.

This study, focusing on deep learning, implements and tests five key methodologies to address its research question: 1) Currency exchange rate processing, 2) Logistic regression, 3) Linear regression, 4) Recurrent neural networks, and 5) Sentiment analysis. While acknowledging the rapid advancements in the field, this study focuses on establishing a strong baseline with established and effective deep learning approaches.

The main contributions of our research are as follows: extending the analysis to a broad spectrum of economic agents, including commercial sectors such as mobile telecommunications, information and communications technology (ICT), and service companies (Pop & Gîfu, 2020; Pop et al., 2021/2022/2023); developing a heterogeneous data corpus, integrating content from social media alongside economic and business news sources; and the prototype system developed within this project, which enhances stock market fluctuation prediction accuracy, providing an advanced decision-support tool for both established and emerging companies.

3. Dataset and method

This section presents a method that analyzes how economic fluctuations are reflected in traditional mass media, including economic publications and specialized forums. It utilizes algorithms trained on a corpus of journalistic texts to identify key factors that can help predict an economic crisis.

3.1 Dataset

The RoNews dataset consists of 33,000 articles from newspapers, covering the period from 2008 to 2018. It is divided into two main categories: *economic* (from reputable economic publications) and *non-economic* (from social media). Each category is further split into three subclasses (see Fig. 1).

```
RoNews
├── Financial-Banking Sector
│    ├── Bank Loans
│    ├── Real Estate Market
│    ├── Capital Market (Budget)
│    └── Exchange Rate
├── IT Industry
└── Leftovers
```

Figure 1. Dataset classes

Exchange Rate: Articles about events related to exchange rate discussions in Romania or abroad.

Capital Market (Budget): News items with data relevant to Romania's stock market, focusing on bank loans, real estate, and the IT industry.

Leftovers or Unclassified Data: Information that doesn't fit the core economic categories but offers valuable contextual insights. For example, cultural events like the Transilvania International Film Festival, while not directly affecting exchange rates or capital markets, may impact tourism and local businesses, contributing to the broader socio-economic landscape.

3.2 Method

For illustration, Figure 2 presents the RoMarketPulse architecture which is based on four modules to be described and exemplified.

Module 1: Data Collection and Acquisition; Article Validation

Data Collection: This module initiates the process by collecting relevant data from diverse online news sources. This encompasses the utilization of web scraping techniques for the extraction of articles from websites, APIs for news feed access, and/or press article databases.

Data Acquisition: Following initial collection, the data is stored in an appropriate format (e.g., TXT) for subsequent processing. This involves the organization of articles within a database, file system, and/or specific data structure.

Article Validation: To ensure data quality, a set of algorithms is applied to verify article coherence. These algorithms include grammar and orthography verification, detection of contradictory or unverified information, and comparison with other news sources to identify potential misinformation or errors.

Module 2: Corpus Segmentation and Article Preprocessing

Corpus Segmentation: Articles are grouped into thematic categories relevant to financial crisis analysis. These include categories such as “economy”, “finance”, “politics”, “social”, etc.

Article Preprocessing: Each article undergoes preprocessing tailored to its respective category. This includes the removal of irrelevant words (stopwords), text normalization (case conversion, punctuation removal), and segmentation into keywords or key phrases (tokenization), among other techniques.

Module 3: Data Preprocessing and Indicator Extraction

Data Preprocessing: This module employs specific algorithms to prepare the data for indicator analysis. This includes numerical data transformation, value scaling, outlier removal, and other relevant data manipulation techniques.

Indicator Extraction: Algorithms are utilized to identify and extract indicators associated with financial crises. These indicators can be of an economic nature (GDP, inflation, unemployment), financial (interest rates, exchange rates, stock market indicators), social (consumer confidence index), or political (political instability, governmental decisions).

```
RoNews Data Processing Workflow

1. Data Ingestion:
   - RoNews News Feed

2. Data Validation & Preparation:
   - Consistency Checking

3. Data Categorization & Preprocessing:
   - Exchange Data
   - Leftovers Preprocessing
   - Budget Preprocessing

4. Analysis:
   - Tuples Processing & RNR Validation
   - Sentiment Analysis
   - Logistic Regression, Linear Regression, RNN

5. Results Generation:
   - Results Output (for each analysis branch)
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Figure 2. Data flow diagram

Module 4: Results Validation and Economic Crisis Prediction

Results Validation: The results obtained from indicator analysis are validated through diverse advanced analytical methods. This includes comparison with historical data, utilization of statistical models to evaluate prediction accuracy, and validation by experts in the field of economics.

Economic Crisis Prediction: Based on the validated results, the economic crisis prediction is generated. This involves the application of machine learning models, neural networks, and/or other artificial intelligence techniques that estimate the probability and timing of an economic crisis.

3.3 NLP pipeline

This section describes the core of the data preparation pipeline, encompassing several crucial steps to transform raw news articles into a format suitable for indicator extraction and subsequent analysis.

The process begins even before traditional “preprocessing” with a vital *Consistency Checking* phase. Before any further processing, a thorough, block-by-block verification is performed to ensure data consistency between the original data source and any replicas. This is crucial because, given the large volume of online news articles from diverse authors, text authenticity cannot be assumed. The consistency checking algorithm (utilizing the *IBM FileNet Consistency Checker*) serves two primary purposes: (1) Validating the authenticity of the RoNews corpus text; (2) Applying a set of preprocessing operations that eliminate duplicate and inconsistent texts.

This step is not merely desirable; it is essential. A significant portion of the original corpus was found to contain inconsistencies, plagiarized content, or even verbatim copies from external sources. The IBM FileNet Consistency Checker (FCC), integrated within FileNet Enterprise Manager (FEM), allows for this vital verification. While typically used for post-disaster recovery, its capabilities are invaluable here. FCC verifies that files in the repository match metadata in the CE database. This tool identifies semantic conflicts such as unused rules, rules lacking equivalents, redundant rules, conflicting rules, and conflicts between decision tables and trees. Specifically, it analyzes conflicts, redundancies, and equivalencies between rows in the same or different decision tables, leaves in the same or different decision trees, and combinations of rows, leaves, and action rules. As a direct result of this consistency check, the initial corpus was reduced from 33,000 to 30,800 articles, with the foreign exchange and real estate market sectors being most heavily impacted (2,200 articles removed due to duplication and inconsistency).

After consistency verification does the *standard preprocessing chain* begin. This phase starts with text segmentation and proceeds through tokenization, lemmatization, and part-of-speech (POS) tagging, leveraging the TreeTagger tool within the Python NLTK (Natural Language Toolkit) library.

The process involves:

1. Extracting content from the source TXT file (using UTF-8 encoding for Romanian diachritics recognition);
2. Data cleaning (removing links and extraneous symbols);
3. Syntactic analysis using the TreeTagger POS-tagger.

For exchange rate information, additional specialized steps are necessary: extracting potential date and monetary value indicators (RON, EUR, USD); identifying text events that can be linked to dates; and extracting numerical representations of monetary values in various currencies.

3.4 Method

Three submodules were considered, corresponding to each category in the RoNews corpus:

3.4.1 Exchange rate market

The first step was to extract all tuples of the form `<date, value in euros, value in dollars>` from the exchange rate dataset by applying the NBR (National Bank of Romania) validation algorithm.

It is important to note that the National Bank of Romania publishes monthly an XML file containing detailed information about the daily exchange rate of currencies for a period of 15 years. This data is essential for analyzing currency fluctuations and for validating information from various sources. After applying the NBR validation algorithm, it was found that a very small number of values were incorrect. Thus, about 20 tuples were removed from the initial set due to identified inconsistencies.

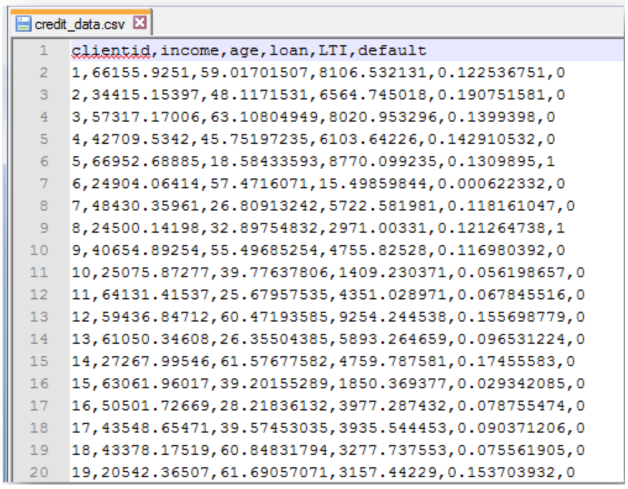
The results obtained after the NBR validation were carefully checked and, finally, all the correct data were stored in a CSV file, thus ensuring a solid database for the next steps of the analysis. This verified data is essential for any further processing or integration into other financial analysis systems.

3.4.2 Capital market

This module focuses on analyzing data from the RoNews corpus, classified under the “budget” category. The data was divided into three distinct subcategories, each with specific characteristics and processing algorithms: information on bank loans, real estate market data, and IT industry data.

A dedicated algorithm was applied for each of these subcategories:

- **Logistic Regression for bank loans** was implemented using Python 3.7, based on essential libraries such as python. Pandas and python.Sklearn. Logistic regression is a statistical model used to estimate the probability of a particular event, given the independent variables (relevant factors) that influence the dependent variable (what we want to predict). The algorithm measures the relationship between the input features and the desired outcome, thus allowing the estimation of precise probabilities in the context of bank loan prediction. The application of this algorithm took place on a set of approximately 7,330 files containing information about bank loans. After preprocessing and validation, 3,770 files were retained, considered to be correctly extracted and relevant for further analysis. After the preprocessing process, we have a CSV file which was used to train the logistic regression algorithm, thus ensuring a robust database for making accurate predictions and analyzing trends in the banking sector.
- **Linear Regression** for the real estate market was implemented in Python 3.7, similar to the previous approach. The algorithm was applied to a dataset comprising approximately 3,660 files related to real estate market transactions. After applying the extraction and validation process, only 2,240 files were correctly extracted and considered relevant for the real estate market analysis, thus ensuring the accuracy of the data used in the linear regression model. This algorithm is ideal for understanding the relationships between the various economic variables involved in real estate transactions and for predicting future developments based on them.


credit_data.csv

```
clientid,income,age,loan,LTI,default
1,66155.9251,59.01701507,8106.532131,0.122536751,0
2,34415.15397,48.1171531,6564.745018,0.190751581,0
3,57317.17006,63.10804949,8020.953296,0.1399398,0
4,42709.5342,45.75197235,6103.64226,0.142910532,0
5,66952.68885,18.58433593,8770.099235,0.1309895,1
6,24904.06414,57.4716071,15.49859844,0.000622332,0
7,48430.35961,26.80913242,5722.581981,0.118161047,0
8,24500.14198,32.89754832,2971.00331,0.121264738,1
9,40654.89254,55.49685254,4755.82528,0.116980392,0
10,25075.87277,39.77637806,1409.230371,0.056198657,0
11,64131.41537,25.67957535,4351.028971,0.067845516,0
12,59436.84712,60.47193585,9254.244538,0.155698779,0
13,61050.34608,26.35504385,5893.264659,0.096531224,0
14,27267.99546,61.57677582,4759.787581,0.17455583,0
15,63061.96017,39.20155289,1850.369377,0.029342085,0
16,50501.72669,28.21836132,3977.287432,0.078755474,0
17,43548.65471,39.57453035,3935.544453,0.090371206,0
18,43378.17519,60.84831794,3277.737553,0.075561905,0
19,20542.36507,61.69057071,3157.44229,0.153703932,0
```

Figure 3. CSV file containing information about bank credits

Recurrent Neural Networks (RNNs) for the IT industry were implemented using the Python TensorFlow framework, which is very efficient in managing sequential data. RNNs are able to capture the temporal dependencies between the input data, which makes them ideal for analyzing news flows and financial market developments. However, during training, special attention was paid to managing the multiplication of gradients smaller than zero, to prevent learning errors and the phenomenon of vanishing gradient. The algorithm was trained on a set of approximately 4,400 news articles in the IT field, including relevant information about the IT industry and specific stock market indices for this sector. By applying recurrent neural networks, it was possible to identify significant trends in the evolution of this sector, providing useful and accurate forecasts in the context of the IT stock market.

3.4.3 Leftovers

This category includes approximately 6,960 files that could not be assigned to other economic categories mentioned previously. For the analysis of the files in the "leftovers" dataset, the use of sentiment analysis (SA) was chosen as an appropriate method. The implementation of sentiment analysis was carried out in Python, using a set of libraries, including Polyglot. Polyglot has polarity lexicons for 136 languages, including Romanian, and the polarity scale of words is based on three levels: +1 for positive words, -1 for negative words, and 0 for neutral words. This Python module proves useful in calculating a more precise score of the sentiment associated with an entity mentioned in a text. If the predominant sentiment is negative, specialists consider that news a signal of a possible economic crisis, given the context and nuances transmitted by the text.

4. Statistics

The prediction performance of the exchange rate processing algorithm (including NBR validation), the logistic regression algorithm, the linear regression algorithm, the recurrent neural network (RNN), the sentiment analysis model, and the RoMarketPulse result based on these algorithms are presented in Table 1.

Table 1. Values (Training Set)

Method	Precision	Recall	Accuracy
Exchange rate processing	0.78	0.78	0.78
Logistic Regression	0.74	0.73	0.77
Linear Regression	0.78	0.80	0.78
Recurrent Neural Network	0.73	0.75	0.73
Sentiment Analysis	0.85	0.81	**0.85**

This study (using training data from Table 1) evaluated several methods for economic prediction. Sentiment analysis performed best (around 85% accuracy), likely due to its ability to capture market sentiment from news and social media. Linear regression and exchange rate processing achieved good results (around 78 accuracy), suggesting strong correlations between economic indicators and target variables. Logistic regression had moderate performance (around 77% accuracy), possibly less suited to the data's complexity. Recurrent Neural Networks (RNNs) performed the worst (around 73% accuracy), potentially due to data limitations, the complexity of economic systems, overfitting, or suboptimal hyperparameter tuning. The study concludes that combining these methods, especially sentiment analysis with traditional statistical approaches, could create a more robust economic prediction system.

5. Conclusions

This research proposes a method for anticipating economic trends by analyzing past economic events, using a decade's worth of economic news articles from the ronews dataset. this approach has identified signs of the 2020 global economic crisis (COVID-19 pandemic) within the data, acknowledging a roughly two-year margin of error for such studies. The research aims to provide a valuable tool for decision-makers and contribute to building interactive economic study platforms for financial expertise and accessible economic education. Furthermore, it emphasizes the role of elearning and collaboration between economists, programmers, and nlp specialists in creating intuitive online platforms to make financial learning more accessible and relevant for the evolving global economy.

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