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Department of Computer Science

Unmasking Deception through Advanced NLP Analysis (Bidirectional LSTM)

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Master of Science in *Computer Science*

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Declaration

I, Najeebuddin Mohammed, of the Department of Computer Science, Texas A&M University - Commerce, confirm that this is my own work and figures, tables, equations, code snippets, artworks, and illustrations in this report are original and have not been taken from any other person's work, except where the works of others have been explicitly acknowledged, quoted, and referenced. I understand that if failing to do so will be considered a case of plagiarism. Plagiarism is a form of academic misconduct and will be penalised accordingly.

I give consent to a copy of my report being shared with future students as an exemplar.

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Najeebuddin Mohammed
April 7, 2024

Abstract

The proliferation of misinformation, particularly in the form of fake news, has become a significant challenge in today's digital age. This research project aims to leverage Natural Language Processing (NLP) techniques and machine learning algorithms to detect and combat the spread of deceptive content in online news articles. By analyzing linguistic patterns and employing sentiment analysis, the study seeks to develop a robust framework for accurately identifying fake news articles. The research objectives include analyzing and preprocessing a corpus of news articles, developing a Long Short-Term Memory (LSTM) model for binary categorization, and evaluating the effectiveness of NLP techniques in detecting fake news sources. Through this investigation, the project aims to contribute to the development of reliable mechanisms for combating misinformation and promoting information integrity in online platforms.

Keywords: fake news detection, natural language processing (NLP), machine learning, classifier comparison, text analysis

Acknowledgements

An acknowledgements section is optional. You may like to acknowledge the support and help of your supervisor(s), friends, or any other person(s), department(s), institute(s), etc. If you have been provided specific facility from department/school acknowledged so.

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SMPCS School of Mathematical, Physical and Computational Sciences

Chapter 1

Introduction

1.1 Background

The pervasive dissemination of misinformation in online articles presents a critical challenge in today's information landscape. This project delves into the intersection of Natural Language Processing (NLP) and machine learning to address this issue. Motivated by the increasing impact of fake news on public perception and decision-making, the project seeks to contribute to the development of robust mechanisms for detecting and mitigating the spread of deceptive content.

1.2 Problem statement

Despite advancements in fake news detection techniques, accurately identifying deceptive content in online articles remains a significant challenge. Traditional machine learning approaches often struggle to capture the nuanced linguistic patterns and contextual information present in text data, leading to suboptimal performance in distinguishing between real and fake news articles. Therefore, there is a need to explore more sophisticated methods, such as LSTM networks, to improve the accuracy and effectiveness of fake news detection. The dataset utilized in this research, referred to as the ISOT Fake News Dataset (2018)

1.3 Aims and objectives

Aims: To enhance the precision of fake news detection within a corpus of news articles in Dataset (2018) using LSTM networks.

Objectives:

1. Evaluate the effectiveness of LSTM networks in discerning distinctive linguistic patterns associated with fake news sources within the defined news article corpus.(Dataset, 2018)
2. Investigate the impact of LSTM-based models on improving the accuracy of fake news detection compared to traditional machine learning approaches.
3. Explore techniques for optimizing LSTM architectures, including hyperparameter tuning and model regularization, to achieve better performance in fake news classification tasks.

1.4 Solution approach

The solution approach involves leveraging LSTM networks as the primary technique for fake news detection in online articles. The methodology includes the following steps:

1. Preprocessing and tokenization of the fake news corpus to prepare the text data for LSTM modeling.
2. Designing and training LSTM-based deep learning models for binary classification of news articles into real or fake categories.
3. Fine-tuning the LSTM architectures and experimenting with different configurations to optimize model performance.
4. Evaluating the trained LSTM models using standard evaluation metrics and comparing their performance against baseline models and traditional machine learning algorithms.
5. Analyzing the results to assess the effectiveness of LSTM networks in addressing the fake news detection problem and identifying areas for further improvement.

1.5 Summary of contributions and achievements

Chapter 2

Literature Review

The realm of social media, encompassing forums, social networking, microblogging, social bookmarking, and wikis (*Using Social Media*, n.d., Gil, 2019), significantly influences the dynamics of information dissemination. However, the unintentional factors contributing to the rise of fake news, as evidenced by incidents like the Nepal Earthquake case (Tandoc Jr et al., 2017, Radianti et al., 2016), underline the intricacies of navigating the digital information landscape. In 2020, the global health sector encountered a substantial surge in fake news, prompting the World Health Organization (WHO) to declare an 'infodemic' during the COVID-19 outbreak. This infodemic involved a flood of both authentic and false information, including a noteworthy volume of misinformation.

In response to the challenges of identifying and combating fake news, several research initiatives have proposed innovative solutions. Sahoo and Gupta (2021) introduced an automatic fake news identification technique tailored for the Chrome environment, providing a means to detect fake news on Facebook. This approach leverages various features associated with a Facebook account, coupled with news content features, utilizing deep learning to analyze account characteristics.

FakeNewsNet, presented by Shu et al. (2020), serves as a valuable repository of fake news data. This resource provides datasets with diverse features, spatiotemporal information, and social context, facilitating research in the domain of fake news. Evaluation indicates that user engagements can contribute to fake news detection in addition to news articles, highlighting the multifaceted nature of information dissemination.

Kumar et al. (2020) proposed a CNN and bidirectional LSTM ensembled network for identifying original and false news instances. Utilizing various advanced approaches, such as Long Short Term Memories LSTMs, Convolutional Neural Networks CNNs, attention mechanisms, and ensemble methods, the study collected news instances from sources like PolitiFact. The CNN and bidirectional LSTM ensembled network, incorporating an attention mechanism, demonstrated superior accuracy, emphasizing the significance of model complexity in addressing the fake news identification challenge.

Natural Language Processing (NLP) emerges as a pivotal tool in tackling fake news. Choudhary and Arora (2021) proposed a linguistic model, employing handcrafted linguistic features for fake news detection. The model, driven by language-specific features, demonstrated a remarkable 86% accuracy in detecting and categorizing fake messages. Additionally, Abdullah et al. (2020) adopted a multimodal approach, combining Convolutional Neural Network (CNN) and

Long Short-Term Memory (LSTM), achieving significant performance in classifying fake news articles based on source, history, and linguistic cues.

Furthermore, Aslam et al. (2021) introduced an ensemble-based deep learning model for classifying news as fake or real using the LIAR dataset. Employing a combination of Bi-LSTM-GRU- dense and dense deep learning models, the study achieved notable accuracy, recall, precision, and F-score. Despite these advancements, ongoing research aims to enhance the robustness of these models, emphasizing the need for continual improvement and exploration of diverse datasets in fake news detection.

2.1 Evaluation of Existing Scholarship on Fake News Detection

The comprehensive examination of the literature reveals a multifaceted landscape in the realm of fake news identification. Researchers employ diverse strategies, ranging from linguistic models to multimodal approaches, emphasizing the need for a holistic understanding that incorporates both content and social context. Key findings underscore the significance of model complexity, with advanced architectures like the CNN bidirectional LSTM ensembled network exhibiting notable success. Natural Language Processing (NLP) emerges as a critical tool in deciphering news content, demonstrated by linguistic models and the utilization of NLP techniques for textual attribute analysis. Despite considerable progress, there remains a persistent call for improvement, urging researchers to explore feature richness, latent semantic features, and diverse datasets. The global impact of infodemics, particularly highlighted during the COVID-19 outbreak, underscores the urgency in developing robust fake news detection systems. In essence, the literature review illuminates the dynamic and evolving nature of fake news research, emphasizing innovation and adaptability in response to the challenges presented in the digital information age.

2.2 Summary

In summary, this literature review provides a comprehensive exploration of the current state of research in the field of fake news detection. The chapter commences by delineating the landscape of social media and its role in the dissemination of misinformation. It delves into the inadvertent factors contributing to the emergence of fake news, exemplifying instances such as the Nepal Earthquake case. The review accentuates the gravity of the 'infodemic,' particularly evident during the COVID-19 outbreak, necessitating advanced detection mechanisms. Several notable research endeavors are scrutinized, including Sahoo and Gupta (2021) automatic fake news identification technique, Shu et al. (2020) repository, and Kumar et al. (2020) CNN+bidirectional LSTM ensembled network. The significance of Natural Language Processing (NLP) in understanding and detecting fake news is highlighted through studies like Choudhary and Arora (2021) linguistic model. The literature underscores the need for continuous innovation, feature exploration, and adaptation to address the evolving challenges posed by the rampant spread of fake news. This synthesis of existing knowledge provides a robust foundation for the ensuing research endeavors aimed at enhancing the efficacy of fake news detection systems.

Chapter 3

Methodology

Data Collection

The ISOT Fake News Dataset serves as the foundation for this research endeavor, comprising articles categorized into real and fake news. Through meticulous collection efforts, articles were sourced from reputable platforms like Reuters.com for truthful content and flagged unreliable sources for fake news articles. The dataset's temporal focus on articles primarily from 2016 to 2017 aligns with a period marked by significant political discourse, making it particularly relevant for studying misinformation dynamics.

Consisting of two CSV files, "True.csv" and "Fake.csv," the dataset offers over 12,600 articles each, providing a rich and diverse collection for analysis. Each article within the dataset includes essential information such as the article title, text, publication date, and categorization as real or fake news. By retaining certain characteristics of fake news articles, such as punctuation and mistakes, the dataset aims to authentically reflect the nature of misinformation encountered in real-world contexts, ensuring its relevance and utility for research purposes.

Data Preprocessing

In the text preprocessing phase, several operations are conducted to refine the dataset for subsequent analysis. Initially, class labels are assigned to distinguish between real and fake news articles, with real articles labeled as class 1 and fake articles as class 0. Next, the title and text content of each article are combined into a single cohesive body to streamline the text processing pipeline. This consolidation enhances the effectiveness of subsequent natural language processing (NLP) tasks by providing a unified textual representation for analysis.

Furthermore, certain attributes that do not contribute significantly to the analysis are removed from the dataset. Specifically, the subject field, which differs between real and fake articles, is dropped, along with the date, title, and publisher information for real articles. This pruning of extraneous attributes streamlines the dataset and focuses attention on the essential text content and class labels. Finally, the processed real and fake datasets are merged into a single dataframe, enabling comprehensive analysis and modeling of the combined dataset. The resultant dataframe, denoted as 'df,' encapsulates the consolidated dataset, ready for further exploration and modeling.

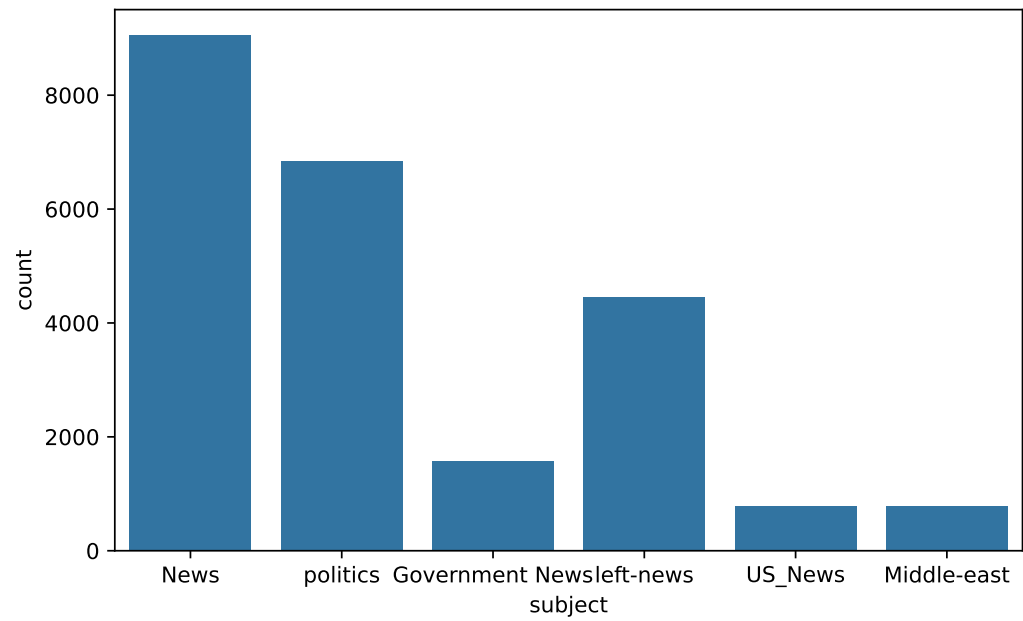


Figure 3.1: Fake News Categories

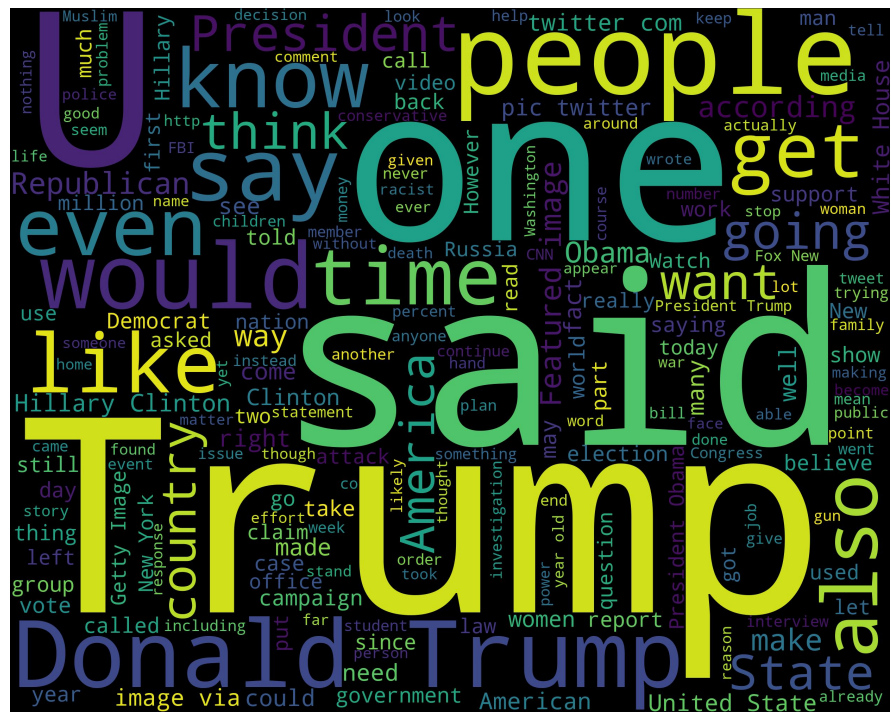


Figure 3.2: Fake News - word Cloud

Feature Engineering

In the feature engineering process, the raw text data is preprocessed and transformed into numerical representations suitable for training machine learning models. Initially, the text is tokenized and cleaned to remove punctuation, stopwords, and other irrelevant characters using the NLTK library. This preprocessing step ensures that the text data is in a standardized format and free from noise that could potentially interfere with the learning process. Subsequently, Word2Vec embeddings are generated using the Gensim library, which learns distributed representations of words by capturing their semantic and syntactic relationships. These word embeddings encode rich semantic information and enable the modeling of word context, similarity, and association within the textual data.

Furthermore, the tokenized text sequences are converted into numerical sequences using a tokenizer, where each word is mapped to a unique numerical identifier. These numerical representations facilitate the input of text data into deep learning models such as recurrent neural networks (RNNs) or convolutional neural networks (CNNs). To ensure uniform input dimensions, the text sequences are padded or truncated to a fixed length, allowing for efficient processing within the neural network architecture. By transforming the raw text into numerical sequences and embedding them into a continuous vector space, the feature engineering phase lays the groundwork for training robust machine learning models capable of capturing intricate patterns and relationships within the textual data.

Model Selection

The chosen neural network architecture for this research project integrates an embedding layer initialized with pre-trained Word2Vec embeddings, followed by an LSTM layer and a dense layer for binary classification. By leveraging pre-trained embeddings, the model can effectively capture semantic information and contextual relationships within the news articles. This initialization ensures that words with similar meanings are represented closer in the embedding space, facilitating the model's ability to understand the underlying semantics of the text. Subsequently, the LSTM layer is incorporated to handle the sequential nature of the input data, enabling the model to capture temporal dependencies and long-term patterns within the text. LSTM networks are particularly well-suited for processing sequential data and have demonstrated effectiveness in various NLP tasks, making them a suitable choice for this classification task.

The addition of a dense layer with a sigmoid activation function allows the model to perform binary classification, predicting the likelihood of a news article being real or fake. By outputting a probability score between 0 and 1, the model can effectively differentiate between the two classes. The binary cross-entropy loss function is employed to optimize the model parameters during training, while accuracy serves as the evaluation metric to assess the model's performance. This architecture strikes a balance between capturing semantic relationships, modeling sequential data, and performing binary classification, thereby demonstrating its efficacy in classifying news articles while considering the complex linguistic structure and contextual nuances present in the text data.

Model Training and Evaluation

The dataset was split into training and testing sets using the train test split function, with a default ratio of 75% for training and 25% for testing. The model was then trained on the training data

for a total of 7 epochs, during which the neural network's parameters were adjusted iteratively to minimize the loss between the predicted and actual class labels. The training process involved monitoring the model's performance on a validation subset, comprising 30% of the training data, to prevent overfitting and ensure generalization.

Chapter 4

Results

The results chapter tells a reader about your findings based on the methodology you have used to solve the investigated problem. For example:

- If your project aims to develop a software/web application, the results may be the developed software/system/performance of the system, etc., obtained using a relevant methodological approach in software engineering.
- If your project aims to implement an algorithm for its analysis, the results may be the performance of the algorithm obtained using a relevant experiment design.
- If your project aims to solve some problems/research questions over a collected dataset, the results may be the findings obtained using the applied tools/algorithms/etc.

Arrange your results and findings in a logical sequence.

4.1 A section

...

4.2 Example of a Table in L^AT_EX

Table 4.1 is an example of a table created using the package L^AT_EX “booktabs.” do check the link: wikibooks.org/wiki/LaTeX/Tables for more details. A table should be clean and readable. Unnecessary horizontal lines and vertical lines in tables make them unreadable and messy. The example in Table 4.1 uses a minimum number of liens (only necessary ones). Make sure that the top rule and bottom rule (top and bottom horizontal lines) of a table are present.

Table 4.1: Example of a table in L^AT_EX

Bike		
Type	Color	Price (£)
Electric	black	700
Hybrid	blue	500
Road	blue	300
Mountain	red	300
Folding	black	500

4.3 Example of captions style

- The **caption of a Figure (artwork)** goes **below** the artwork (Figure/Graphics/illustration). See example artwork in Figure ??.
- The **caption of a Table** goes **above** the table. See the example in Table 4.1.
- The **caption of an Algorithm** goes **above** the algorithm. See the example in Algorithm ??.
- The **caption of a Listing** goes **below** the Listing (Code snippet). See example listing in Listing ??.

4.4 Summary

Write a summary of this chapter.

Chapter 5

Discussion and Analysis

Depending on the type of project you are doing, this chapter can be merged with “Results” Chapter as “ Results and Discussion” as suggested by your supervisor.

In the case of software development and the standalone applications, describe the significance of the obtained results/performance of the system.

5.1 A section

Discussion and analysis chapter evaluates and analyses the results. It interprets the obtained results.

5.2 Significance of the findings

In this chapter, you should also try to discuss the significance of the results and key findings, in order to enhance the reader’s understanding of the investigated problem

5.3 Limitations

Discuss the key limitations and potential implications or improvements of the findings.

5.4 Summary

Write a summary of this chapter.

Chapter 6

Conclusions and Future Work

6.1 Conclusions

Typically a conclusions chapter first summarizes the investigated problem and its aims and objectives. It summarizes the critical/significant/major findings/results about the aims and objectives that have been obtained by applying the key methods/implementations/experiment set-ups. A conclusions chapter draws a picture/outline of your project's central and the most significant contributions and achievements.

A good conclusions summary could be approximately 300–500 words long, but this is just a recommendation.

A conclusions chapter followed by an abstract is the last things you write in your project report.

6.2 Future work

This section should refer to Chapter 4 where the author has reflected their criticality about their own solution. The future work is then sensibly proposed in this section.

Guidance on writing future work: While working on a project, you gain experience and learn the potential of your project and its future works. Discuss the future work of the project in technical terms. This has to be based on what has not been yet achieved in comparison to what you had initially planned and what you have learned from the project. Describe to a reader what future work(s) can be started from the things you have completed. This includes identifying what has not been achieved and what could be achieved.

A good future work summary could be approximately 300–500 words long, but this is just a recommendation.

Chapter 7

Reflection

Write a short paragraph on the substantial learning experience. This can include your decision-making approach in problem-solving.

Some hints: You obviously learned how to use different programming languages, write reports in \LaTeX and use other technical tools. In this section, we are more interested in what you thought about the experience. Take some time to think and reflect on your individual project as an experience, rather than just a list of technical skills and knowledge. You may describe things you have learned from the research approach and strategy, the process of identifying and solving a problem, the process research inquiry, and the understanding of the impact of the project on your learning experience and future work.

Also think in terms of:

- what knowledge and skills you have developed
- what challenges you faced, but was not able to overcome
- what you could do this project differently if the same or similar problem would come
- rationalize the divisions from your initial planned aims and objectives.

A good reflective summary could be approximately 300–500 words long, but this is just a recommendation.

Note: The next chapter is “**References**,” which will be automatically generated if you are using BibTeX referencing method. This template uses BibTeX referencing. Also, note that there is difference between “References” and “Bibliography.” The list of “References” strictly only contain the list of articles, paper, and content you have cited (i.e., refereed) in the report. Whereas Bibliography is a list that contains the list of articles, paper, and content you have cited in the report plus the list of articles, paper, and content you have read in order to gain knowledge from. We recommend to use only the list of “References.”

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Appendix A

An Appendix Chapter (Optional)

Some lengthy tables, codes, raw data, length proofs, etc. which are **very important but not essential part** of the project report goes into an Appendix. An appendix is something a reader would consult if he/she needs extra information and a more comprehensive understating of the report. Also, note that you should use one appendix for one idea.

An appendix is optional. If you feel you do not need to include an appendix in your report, avoid including it. Sometime including irrelevant and unnecessary materials in the Appendices may unreasonably increase the total number of pages in your report and distract the reader.

Appendix B

An Appendix Chapter (Optional)

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