

Identifying Nuances in Sentiment and Claimed Words to Spot Yellow Journalism

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CERTIFICATE OF RECOMMENDATION

To Whom It May Concern

I hereby recommend that the project report entitled “Identifying Nuances in Sentiment and Claimed Words to Spot Yellow Journalism” has been carried out by Chandrayee Mandal (Reg. No.: 163637 of 2022-23, Roll No.: 002210503045, Exam Roll: MCA244044), under my guidance and supervision and be accepted in partial fulfilment of the requirement for the degree of Master of COMPUTER APPLICATION in DEPARTMENT of COMPUTER SCIENCE and ENGINEERING, JADAVPUR UNIVERSITY during the academic year 2023-2024.

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This is to certify that the project report entitled “**Identifying Nuances in Sentiment and Claimed Words to Spot Yellow Journalism**” is a bonafide record of work carried out by CHANDRAYEE MANDAL , in fulfillment of the requirements for the award of the degree of Master of Computer Application in the Department of Computer Science and Engineering, Jadavpur University. It is understood that by this approval the undersigned do not necessarily endorse or approve any statement made, opinion expressed or conclusion drawn therein but approve the project report only for the purpose for which it has been submitted.

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**DECLARATION OF COMPLIANCE WITH
ACADEMIC ETHICS**

I hereby declare that this project report entitled "Identifying Nuances in Sentiment and Claimed Words to Spot Yellow Journalism" is an outcome of my genuine and independent work, as part of my Master of Computer Application program.

All information in this document has been obtained and presented in accordance with academic rules and ethical conduct.

I also declare that, as required by these rules and conduct, all materials and results that are not original to this work have been fully cited and referenced.

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Chandrayee Mandal

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ABSTRACT

This research delves into the realm of media integrity, focusing on the detection of yellow journalism through nuanced sentiment analysis and claim identification. A manual dataset preparation approach ensures granularity and accuracy. Leveraging Support Vector Machines (SVM) and Bidirectional Long Short-Term Memory (BiLSTM) networks, the study endeavours to elucidate the intricate interplay between claimed words and sentiment in journalistic content.

The methodology involves meticulous claim and sentiment identification, followed by a rigorous analysis of their relationships. By employing both traditional SVM classifiers and cutting-edge BiLSTM architectures, the research aims to not only detect but also understand the underlying mechanisms of yellow journalism. Through meticulous evaluation and interpretation, the study sheds light on the effectiveness of these techniques in combating misinformation and preserving media integrity.

This interdisciplinary approach advances the field of sentiment analysis and claim identification, underscoring the significance of nuanced understanding in combating the spread of misleading information.

CHAPTER 1: INTRODUCTION

1.1. Overview

In today's digital world, where false information spreads quickly, finding reliable sources has become really important. Yellow journalism, which twists facts to influence what people think, is a big problem for honest news and even democracy. To tackle this issue, this project looks into sentiment analysis and claim identification. These are important because they help us understand how people feel about certain claims and how those claims might be spreading false information.

the first phase began by gathering diverse datasets from reliable sources to encompass a broad spectrum of claims and sentiments. These datasets were meticulously prepared to remove inconsistencies and biases, ensuring data integrity. Following preparation, extensive preprocessing techniques were applied to clean and standardize the dataset, including tokenization and removal of stopwords. This rigorous approach set the stage for accurate analysis in subsequent project phases.

After preparing the dataset, the project moved on to two main tasks: identifying claims and analysing sentiment. Claim identification involved sorting statements, while sentiment analysis looked at the emotions expressed. The goal was to see how claims and sentiments relate to each other, revealing insights into their connection in media content.

1.2. Background and Motivation

In the contemporary landscape characterized by the proliferation of misinformation, the imperative to combat deceptive content, particularly within the domain of yellow journalism, underscores the necessity for advanced methodologies. Central to this endeavour is the undertaking of sentiment analysis and claim detection. Sentiment analysis provides insights into the emotional undercurrents embedded within media content, while claim detection enables the identification and classification of specific assertions made within such content. The motivation lies in unravelling the intricate relationship between sentiments expressed and claims made, offering invaluable insights into the mechanisms underpinning misinformation dissemination. This exploration seeks to equip stakeholders with the tools necessary to effectively navigate and counter the pervasive influence of deceptive narratives.

1.Detecting Misinformation: In the realm of yellow journalism, the rise of misinformation necessitates precise methods for identifying deceptive claims and understanding the sentiments conveyed in media content.

2.Sentiment Analysis and Claim Detection: Utilizing techniques like Bidirectional Long Short-Term Memory (BiLSTM) networks and Support Vector Machines (SVM), we analyze sentiments and detect claims within media content, employing manually curated datasets tailored to yellow journalism intricacies.

3.Investigating Relationships: Our research scrutinizes the interplay between expressed sentiments and claims made within yellow journalism. Through analysis of sentiment and claim detection outputs, we seek to reveal correlations that shed light on the influence of sentiments

1.3 Objective

The primary objective of this research is to develop a comprehensive understanding of the relationship between sentiment analysis and claim detection within the context of yellow journalism. Through meticulous dataset curation and the application of advanced machine learning techniques, our aim is to accurately identify deceptive claims and discern the underlying sentiments expressed in media content. By analysing the outputs of sentiment analysis and claim detection models, we seek to uncover patterns and correlations that elucidate how specific sentiments may influence or be influenced by certain claims. Ultimately, this exploration will contribute to our knowledge of the mechanisms driving misinformation dissemination and inform strategies to combat its spread.

1.4 Contributions

This work makes significant contributions to the field of claim verification and sentiment analysis and the relation between them.

First, the it began with the meticulous manual curation of datasets, a process personally undertaken to ensure the inclusion of diverse media content that encapsulated a broad spectrum of claims prevalent in yellow journalism.

Second, sophisticated machine learning techniques, including Support Vector Machines (SVM) for claim detection and sentiment analysis employing Bidirectional Long Short-Term Memory (BiLSTM) networks, were employed. These techniques facilitated the precise identification and categorization of claims within the curated datasets, alongside discerning the underlying sentiments expressed.

third, leveraging these methodologies, a thorough examination of the emotional undercurrents inherent in the media content was conducted, shedding light on the prevailing sentiments underlying the identified claims.

Finally, a comprehensive comparative analysis of the results obtained from these models was conducted, providing valuable insights into their performance and identifying potential areas for improvement.

1.5 Outline of the Report:

The report compares the performance of Support Vector Machine (SVM) in claim detection and Bidirectional LSTM (BiLSTM) in relation analysis. SVM demonstrates high precision for both "no claim" and "claim" categories, yet its recall for "claim" instances is relatively lower, resulting in a lower F1-score. Conversely, BiLSTM excels in relation analysis, exhibiting balanced precision and recall for both "no relation" and "relation" categories, leading to robust F1-scores. BiLSTM achieves a slightly higher accuracy compared to SVM. These findings suggest that while SVM performs well in detecting claims, BiLSTM is more adept at relation analysis. The report outlines the methodology, presents detailed results for both tasks, discusses the comparative analysis, and concludes with

recommendations for model selection based on task requirements and potential avenues for future research.

CHAPTER 2: LITERATURE SURVEY

Sentiment Analysis:

Sentiment analysis is the process of determining the emotional tone of text, categorizing it as positive, negative, or neutral. It's crucial for understanding public opinion and consumer feedback. In yellow journalism, sentiment analysis helps identify biased language. BILSTM and SVM models are commonly used for their effectiveness in capturing context.

Claim Detection:

Claim detection involves identifying statements within text that assert a particular claim or assertion. It's essential for fact-checking and combating misinformation. In yellow journalism, claim detection helps identify potentially misleading claims. BILSTM and SVM models are commonly employed for their ability to learn patterns in textual data.

Relation Between Sentiment Analysis and Claim Detection:

Sentiment analysis and claim detection share the goal of extracting insights from text. Sentiment analysis provides emotional context around claims, while claim detection isolates specific assertions. In yellow journalism, integrating these techniques helps journalists analyze claims and understand emotional tones. By combining sentiment analysis and claim detection, journalists can produce more accurate reporting. BILSTM and SVM models enhance efficiency and accuracy in these tasks.

1

Title: "Sentiment Analysis: Capturing Favorability Using Natural Language Processing"
Authors: Bo Pang and Lillian Lee Published in: Proceedings of the International Conference on Computational Linguistics (COLING), 2002

Title: "Fake News Detection on Social Media: A Data Mining Perspective"

Authors: Soroush Vosoughi, Deb Roy, and Sinan Aral

Published in: ACM SIGKDD Explorations Newsletter, 2018

Title: "Aspect-Based Sentiment Analysis: Foundations and Trends" Authors: Bing Liu
Published in: Information Retrieval Journal, 2015

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CHAPTER 3: METHODOLOGY

3.1 Problem Statement

The proliferation of yellow journalism and its dissemination of misinformation pose significant challenges to media integrity and public discourse. In combating this phenomenon, the identification of deceptive claims and the understanding of the sentiments expressed within media content are imperative. However, existing methodologies often struggle to effectively detect and analyze deceptive claims and sentiments in yellow journalism. For instance, manual fact-checking processes are time-consuming and labor-intensive, while traditional sentiment analysis techniques may fail to capture subtle nuances in language. To address these challenges, advanced machine learning techniques such as Support Vector Machines (SVM) and Bidirectional Long Short-Term Memory (BiLSTM) networks can be leveraged for more efficient and accurate detection of deceptive claims and sentiment analysis. For example, SVM models have been successfully used in text classification tasks, including fake news detection, due to their ability to handle high-dimensional data and nonlinear relationships. Similarly, BiLSTM networks, with their ability to capture contextual information and long-term dependencies, have shown promise in sentiment analysis tasks by effectively modelling sequential data. By exploring the intricate relationship between claims and sentiments using these advanced techniques, this research seeks to contribute to the development of robust strategies for combating misinformation and preserving media integrity in the digital age.

3.2.Dataset Preparation:

Objective Identification and Tailoring:

The dataset preparation methodology was meticulously crafted to address the unique requirements inherent in analyzing yellow journalism.

Initial focus was placed on identifying the specific characteristics and patterns associated with yellow journalism, guiding subsequent data collection and processing efforts.

Manual Collection of Diverse Media Content:

A manual approach was adopted to collect a diverse array of media content from reputable sources spanning various mediums such as newspapers, online articles, videos, and social media platforms.

This manual collection process ensured the inclusion of a broad spectrum of topics, viewpoints, and sources, essential for comprehensive analysis.

Thorough Filtering and Removal of Irrelevant Material:

Each piece of collected content underwent rigorous filtering to eliminate duplicates and irrelevant material that could skew the analysis.

Filters were applied based on criteria such as publication date, source credibility, and relevance to yellow journalism themes.

Identification and Extraction of Claims:

Claims, defined as assertions or statements made within the content, were systematically identified and extracted using natural language processing (NLP) techniques.

Specialized algorithms were employed to parse through the filtered content, isolating sentences or phrases that conveyed claims or allegations, a pivotal step in dataset construction.

Capture of Yellow Journalism Characteristics:

During the claim extraction process, particular attention was given to capturing assertions commonly associated with yellow journalism, such as sensationalism, exaggeration, or manipulation of facts.

This meticulous approach ensured that the dataset encompassed a representative sample of yellow journalism content, facilitating robust analysis and model training.

Annotation of Sentiments:

To enrich the dataset with emotional context, sentiments expressed within each claim were meticulously annotated.

Sentiments were categorized as positive, neutral, or negative, enabling a nuanced understanding of the emotional tone prevalent in yellow journalism content.

Verification and Validation Process:

A comprehensive verification process was employed to validate the accuracy and reliability of the dataset.

Claims and sentiments were cross-referenced with multiple sources and fact-checking platforms to mitigate bias and ensure data integrity.

This rigorous validation process bolstered the credibility of the dataset, instilling confidence in its suitability for subsequent analysis and model training.

Finalization of Structured and Annotated Dataset:

Upon completion of the filtering, extraction, and verification processes, the dataset was structured and annotated to facilitate easy accessibility and utilization.

The finalized dataset served as a robust foundation for subsequent analysis, empowering researchers to delve into claim detection and sentiment analysis within the realm of yellow journalism with precision and depth.

3.3 Proposed Technique/Approach

This section of the report outlines the proposed technique and approach used in developing and evaluating models for claim verification and sentiment analysis and find the relation between sentiment and claim . The approach leverages deep learning techniques such as BiLSTM and machine learning techniques such as SVM, applied to a meticulously curated to the dataset.

3.3.1 SVM(Support Vector Machine):

Definition:

Support Vector Machine (SVM) is a supervised learning algorithm employed for classification and regression analysis. Its primary objective is to identify the optimal hyperplane that effectively separates data points into distinct classes or groups, maximizing the margin between different classes. In essence, SVM aims to find the hyperplane that best segregates data points while maintaining the maximum possible margin between the closest data points from each class, commonly known as support vectors.

Working Principles:

Hyperplane: SVM aims to determine the hyperplane that best segregates data points into separate classes. A hyperplane is essentially an $(n-1)$ dimensional subspace that divides an n -dimensional space into two parts. In simpler terms, in a two-dimensional space, a hyperplane translates to a line.

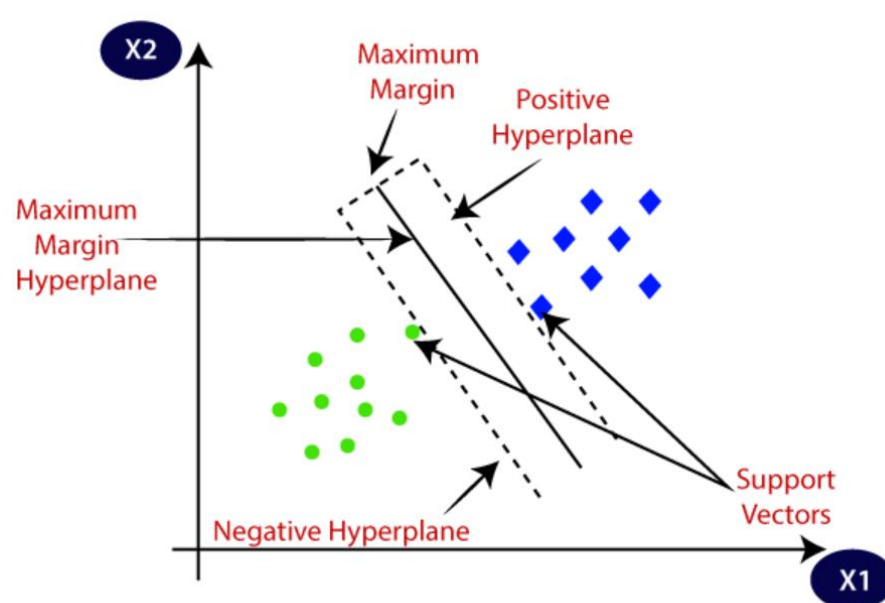
Maximizing Margin: The core concept of SVM revolves around maximizing the margin, which refers to the distance between the hyperplane and the nearest data points from each class, commonly known as support vectors. By maximizing the margin, SVM enhances the generalization capability of the model while mitigating overfitting.

Kernel Trick: SVM effectively deals with non-linearly separable data by employing a technique called the kernel trick. Instead of directly mapping input features into a higher-dimensional space, the kernel function computes the dot product between input features in the higher-dimensional space without explicitly transforming them. This allows SVM to identify non-linear decision boundaries accurately.

Regularization: SVM incorporates a regularization parameter (C) that balances the trade-off between maximizing the margin and minimizing the classification error. A larger C value results in a smaller margin but fewer misclassifications, whereas a smaller C value prioritizes maximizing the margin, even if it leads to more misclassifications.

Classification: Once the optimal hyperplane is established, SVM can classify new data points by determining which side of the hyperplane they fall on. Data points on one side of the hyperplane belong to one class, while data points on the other side belong to the other class.

To illustrate, the unrolled SVM is presented in the figure below:



Advantages of SVM for Claim detection and sentiment analysis:

Effective for High-Dimensional Data: SVM performs exceptionally well in high-dimensional spaces, making it suitable for tasks like claim detection and sentiment analysis that often involve processing large feature sets derived from text data.

Robust to Overfitting: SVM includes a regularization parameter (C) that helps control overfitting by balancing the trade-off between maximizing the margin and minimizing the classification error. This allows SVM to generalize well to unseen data and avoid memorizing noise in the training data.

Non-Linear Decision Boundaries: Through the use of kernel functions, SVM can efficiently model complex, non-linear decision boundaries. This flexibility is crucial for tasks like sentiment analysis, where the relationships between features and sentiment may be non-linear.

Handles Sparse Data: In text-based tasks such as claim detection and sentiment analysis, the data is often sparse due to the large number of features (e.g., words or n-grams) and their occurrences. SVM performs well with sparse data and can handle large feature spaces efficiently.

Binary Classification: SVM naturally lends itself to binary classification tasks, which are common in claim detection and sentiment analysis. By identifying the decision boundary between two classes, SVM can accurately classify new instances as belonging to one class or the other.

Interpretable Results: SVM provides interpretable results by identifying the support vectors, which are the data points closest to the decision boundary. This allows analysts to understand which features contribute most to the classification decision, aiding in the interpretation of results.

Well-Established Theory: SVM is based on well-established theoretical foundations in convex optimization and statistical learning theory. This provides confidence in the algorithm's performance and robustness across different applications.

3.3.2. BiLSTM(Bidirectional Long Short-Term Memory)

Definition:

Bidirectional Long Short-Term Memory (BiLSTM) networks consist of two LSTM layers: one that processes input sequences in the forward direction, and another that processes input sequences in the backward direction. By processing the input sequence in both directions, BiLSTM networks can capture dependencies and patterns that may not be discernible when processing the sequence in only one direction.

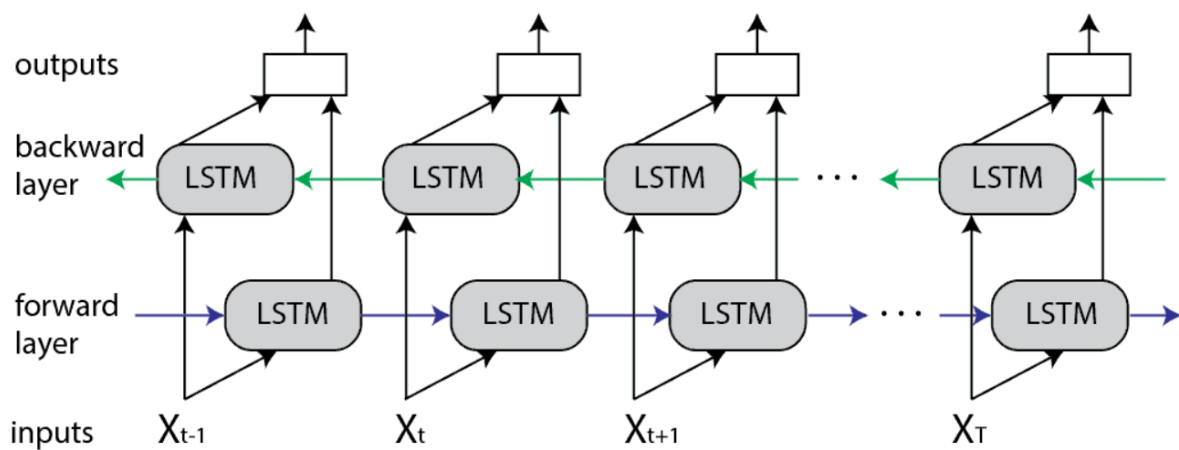
Working Principles:

Forward LSTM: The forward LSTM processes the input sequence from the beginning to the end, capturing dependencies and patterns in the forward direction. At each time step, the LSTM cell receives input from the current time step as well as the output from the previous time step, updating its internal state and producing an output.

Backward LSTM: Conversely, the backward LSTM processes the input sequence from the end to the beginning, capturing dependencies and patterns in the backward direction. Similar to the forward LSTM, it receives input from the current time step as well as the output from the previous time step, updating its internal state and producing an output.

Combining Outputs: The outputs from both the forward and backward LSTMs are concatenated or combined in some manner to produce the final output sequence. This combined output represents a holistic understanding of the input sequence, incorporating information from both forward and backward directions.

To illustrate, the unrolled BiLSTM is presented in the figure below:



Advantages of BiLSTM for Claim detection and sentiment analysis:

Capturing Contextual Dependencies: BiLSTM networks are capable of capturing contextual dependencies in sequential data by processing input sequences in both forward and backward directions. This allows them to understand the context surrounding each word or token in a sentence, which is crucial for tasks like claim detection and sentiment analysis.

Handling Long-Term Dependencies: Traditional LSTM networks suffer from the vanishing gradient problem, which limits their ability to capture long-range dependencies in sequential data. BiLSTM networks mitigate this issue by processing input sequences bidirectionally, enabling them to capture dependencies across longer spans of text.

Improved Representation Learning: BiLSTM networks learn rich representations of input sequences that encapsulate information from both past and future contexts. This enhanced representation learning capability allows them to capture nuanced semantic and syntactic features relevant to claim detection and sentiment analysis tasks.

Modelling Negations and Modifiers: Bidirectional processing enables BiLSTM networks to effectively model negations and modifiers in text. This is particularly important for sentiment analysis, where the presence of negations can reverse the polarity of sentiment expressions.

Flexibility and Adaptability: BiLSTM networks are highly flexible and adaptable to different types of input data and tasks. They can be easily integrated into various architectures and combined with other neural network components to enhance performance on claim detection and sentiment analysis tasks.

CHAPTER 4: EXPERIMENTS AND RESULTS

4.1.1. SVM Model: Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification and regression tasks. In the context of classification, SVM aims to find the optimal hyperplane that separates data points of different classes in feature space. The "support vectors" are the data points closest to the hyperplane and are crucial in defining its position.

Environment Preparation:

- **Libraries:** Import necessary libraries for data manipulation, model building, and evaluation.
 - Pandas: Data manipulation and analysis library.
 - NumPy: Fundamental package for numerical computing.
 - Matplotlib.pyplot: Plotting library for creating visualizations.
 - Seaborn: Statistical data visualization library.
 - train_test_split: Function for splitting data into training and testing sets.
 - SVC: Support Vector Classifier for SVM classification..
- **Dataset:** Load the dataset using Pandas.

Label Encoding:

- **LabelEncoder:** Encode categorical labels into numerical values.

Text Tokenization and Sequence Padding:

- **Tokenizer:** Initialize a tokenizer with a maximum of 20,000 words.
 - **Fit:** Fit the tokenizer on the combined text data.
 - **Text to Sequences:** Convert text data into sequences of integers.
 - **Pad Sequences:** Ensure all sequences have the same length (100).

Label Encoding (One-hot):

- **One-hot Encoding:** Convert numerical labels into a one-hot encoded format using Keras utility.

Data Splitting:

- **Train-Test Split:** Split the data into training and testing sets using an 80-20 split.

- **Model Architecture for Sentiment Analysis:**
 - **Feature Representation:** Each text document is represented as a vector in a high-dimensional space, with features extracted using techniques like bag-of-words or TF-IDF.
 - **Kernel Trick:** SVM maps the input space into a higher-dimensional feature space using the kernel trick, enabling it to find a linear decision boundary even for non-linearly separable data.
 - **Margin Maximization:** SVM aims to find the hyperplane that maximizes the margin between the closest points of different classes, leading to better generalization and model robustness.
 - **Support Vectors:** Support vectors are the data points closest to the decision boundary and are essential for defining it and determining the margin.
 - **Model Training:**
 - The model is trained using labeled training data (X_{train} and $y_{\text{train_sentiment}}$). During training, the SVM algorithm learns to distinguish between different sentiment classes by optimizing a hyperplane that maximizes the margin between the classes in the feature space.
 - **Sentiment Prediction**
 - Once trained, the SVM model is used to predict sentiment labels for unseen test data (X_{test}). The learned decision boundary is applied to classify each instance into one of the sentiment classes.
 - **Model Evaluation**
 - The performance of the SVM model is evaluated using various metrics, including accuracy score and confusion matrix. These metrics provide insights into the model's ability to accurately classify sentiment
-
- **Model Architecture for Claim Detection:**
 - **Feature Representation:** Each text document is represented as a vector in a high-dimensional space, with features extracted using techniques like bag-of-words or TF-IDF.
 - **Kernel Trick:** SVM maps the input space into a higher-dimensional feature space using the kernel trick, enabling it to find a linear decision boundary even for non-linearly separable data.

- **Margin Maximization:** SVM aims to find the hyperplane that maximizes the margin between the closest points of different classes, leading to better generalization and model robustness.
- **Support Vectors:** Support vectors are the data points closest to the decision boundary and are essential for defining it and determining the margin.
- **Model Training:**
 - The model is trained using labeled training data (X_train and y_train_sentiment). During training, the SVM algorithm learns to distinguish between different sentiment classes by optimizing a hyperplane that maximizes the margin between the classes in the feature space.
- **Sentiment Prediction**
 - Once trained, the SVM model is used to predict sentiment labels for unseen test data (X_test). The learned decision boundary is applied to classify each instance into one of the sentiment classes.
- **Model Evaluation**
 - The performance of the SVM model is evaluated using various metrics, including accuracy score and confusion matrix. These metrics provide insights into the model's ability to accurately classify sentiment.

4.1. BiLSTM Model: A Bidirectional Long Short-Term Memory (BiLSTM) model is a type of recurrent neural network (RNN) architecture used for sequence modeling and processing tasks, particularly in natural language processing (NLP) and time series analysis. Here's a breakdown of its components:

Environment Preparation:

- **Libraries:** Import necessary libraries for data manipulation, model building, and evaluation.
 - Pandas: For data manipulation and analysis.
 - Numpy: For numerical operations.
 - Matplotlib and Seaborn: For plotting confusion matrices.
 - Scikit-learn: For splitting the dataset into training and testing sets, and for computing confusion matrices.
 - TensorFlow/Keras: For building and training the LSTM model.
- **Dataset:** Load the dataset using Pandas.

Label Encoding:

- **Label Encoder:** Encode categorical labels into numerical values.

Text Tokenization and Sequence Padding:

- **Tokenizer:** Initialize a tokenizer with a maximum of 20,000 words.
 - **Fit:** Fit the tokenizer on the combined text data.
 - **Text to Sequences:** Convert text data into sequences of integers.
 - **Pad Sequences:** Ensure all sequences have the same length (100).

Label Encoding (One-hot):

- **One-hot Encoding:** Convert numerical labels into a one-hot encoded format using Keras utility.

Data Splitting:

- **Train-Test Split:** Split the data into training and testing sets using an 80-20 split.
- **Model Building For sentiment analysis:**
 - **Architecture:**
 - **Embedding Layer:** Add an embedding layer to convert words into dense vectors of a fixed size. This layer helps in transforming the input text data into numerical form suitable for the neural network.
 - **Bidirectional LSTM Layer:** Add a bidirectional LSTM layer with 64 units. This layer processes the input sequence in both forward and backward directions, capturing dependencies from both ends of the text.
 - **Dense Output Layer:** Add a dense layer with a sigmoid activation function. This layer outputs a single value between 0 and 1, suitable for binary classification tasks.
- **Model Compilation:** Model is configured with optimizer, loss function, and evaluation metric.
- **Model Training:** Trains the model on training data for a specified number of epochs and batch size.
- **Model Evaluation:** Evaluates model performance on testing data to compute loss and accuracy.
- **Prediction and Confusion Matrix:** Makes predictions on testing data and generates confusion matrix for performance assessment.
- **Model Building For Claim Detection:**
 - **Architecture:**
 - **Embedding Layer:** Add an embedding layer to convert words into dense vectors of a fixed size. This layer helps in transforming the

input text data into numerical form suitable for the neural network.

- **Bidirectional LSTM Layer:** Add a bidirectional LSTM layer with 64 units. This layer processes the input sequence in both forward and backward directions, capturing dependencies from both ends of the text.
- **Dense Output Layer:** Add a dense layer with a sigmoid activation function. This layer outputs a single value between 0 and 1, suitable for binary classification tasks.

Model Compilation: Model is configured with optimizer, loss function, and evaluation metric.

Model Training: Trains the model on training data for a specified number of epochs and batch size.

Model Evaluation: Evaluates model performance on testing data to compute loss and accuracy.

Prediction and Confusion Matrix: Makes predictions on testing data and generates confusion matrix for performance assessment.

- **Model Building For Relation Analysis:**

- **Architecture:**

- **Embedding Layer:** Add an embedding layer to convert words into dense vectors of a fixed size. This layer helps in transforming the input text data into numerical form suitable for the neural network.
 - **Bidirectional LSTM Layer:** Add a bidirectional LSTM layer with 64 units. This layer processes the input sequence in both forward and backward directions, capturing dependencies from both ends of the text.
 - **Dense Output Layer:** Add a dense layer with a sigmoid activation function. This layer outputs a single value between 0 and 1, suitable for binary classification tasks.

- **Model Compilation:** Model is configured with optimizer, loss function, and evaluation metric.
- **Model Training:** Trains the model on training data for a specified number of epochs and batch size.

- **Model Evaluation:** Evaluates model performance on testing data to compute loss and accuracy.
- **Prediction and Confusion Matrix:** Makes predictions on testing data and generates confusion matrix for performance assessment.
- **Model Building For claim detection:**
 - **Architecture:**
 - **Embedding Layer:** Add an embedding layer to convert words into dense vectors of a fixed size. This layer helps in transforming the input text data into numerical form suitable for the neural network.
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Model Compilation: Model is configured with optimizer, loss function, and evaluation metric.

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Model Evaluation: Evaluates model performance on testing data to compute loss and accuracy.

Prediction and Confusion Matrix: Makes predictions on testing data and generates confusion matrix for performance assessment.

4.2.Results

4.2.1. Results for classification:

- **Results for Sentiment Analysis using SVM I:**

table 1:

	Precision	recall	F1 Score	Support
Negative	0.71	0.91	0.80	33
Positive	0.84	0.57	0.68	28
Accuracy			0.75	0.61
Macro avg	0.78	0.74	0.74	61
Weighted avg	0.77	0.75	0.75	61

The sentiment analysis model utilizing Support Vector Machine (SVM) classification demonstrates moderate performance across negative and positive sentiment classes. The precision metrics indicate the model's accuracy in classifying sentiment labels, with 0.71 precision for negative sentiment and 0.84 for positive sentiment, suggesting a higher precision in identifying positive sentiment. However, the recall scores present disparities between classes, with 0.91 for negative sentiment and 0.57 for positive sentiment, indicating the model's superior capability in capturing negative sentiment instances. The balanced F1-scores of 0.80 for negative sentiment and 0.68 for positive sentiment highlight the model's effectiveness in achieving a balance between precision and recall. Overall accuracy stands at 0.75, signifying the model's ability to correctly predict sentiment labels for 75% of the test dataset. Macro and weighted averages for precision, recall, and F1-score underscore the model's consistent performance across both sentiment classes, with macro averages at 0.78 precision, 0.74 recall, and 0.74 F1-score, and weighted averages at 0.77 precision, 0.75 recall, and 0.75 F1-score.

- **Results for Sentiment Analysis using BILSTM :**

table 2:

	precision	recall	f1-score	SUPPORTS
Negative	0.91	0.97	0.94	33
Positive	0.96	0.89	0.93	28
accuracy			0.93	61
Macro avg	0.94	0.93	0.93	61
weighted avg	0.94	0.93	0.93	61

The sentiment analysis model demonstrates robust performance in discerning the sentiment polarity of text samples, achieving an overall accuracy of 93%. Precision metrics indicate high levels of correctness in sentiment predictions, with 91% precision for negative sentiment and 96% for positive sentiment, ensuring that the model makes few false positive predictions. Similarly, recall metrics reveal the model's ability to capture the majority of true sentiment instances, with 97% recall for negative sentiment and 89% for positive sentiment. The harmonic mean of precision and recall, represented by the F1-score, is notably high for both sentiment classes, at 94% for negative sentiment and 93% for positive sentiment. These results, alongside support counts reflecting 33 instances of negative sentiment and 28 of positive sentiment, underscore the model's effectiveness across a diverse range of sentiment-labelled samples. The macro average and weighted average metrics further confirm the model's consistent performance across sentiment classes, with scores averaging at 94% precision, 93% recall, and 93% F1-score, highlighting its robustness in sentiment analysis tasks.

- **Results for Claim Detection using SVM :**

table 3:

	Precision	recall	F1 Score	Support
No claim	0.91	1.00	0.95	51
Claim	1.00	0.50	0.67	10
Accuracy			0.92	61
Macro avg	0.96	0.75	0.81	61
Weighted avg	0.93	0.92	0.91	61

The claim detection model employing Support Vector Machine (SVM) classification demonstrates strong performance across "No Claim" and "Claim" classes. Precision scores indicate the model's accuracy in predicting claim labels, with 0.91 precision for "No Claim" and a perfect 1.00 precision for "Claim," suggesting high precision in identifying both classes. However, recall scores differ notably between classes, with 1.00 for "No Claim" and 0.50 for "Claim," indicating the model's superior ability to capture instances of "No Claim" compared to "Claim." The balanced F1-scores of 0.95 for "No Claim" and 0.67 for "Claim" highlight the model's effectiveness in achieving a balance between precision and recall. Overall accuracy stands at 0.92, demonstrating the model's capability to correctly predict claim labels for 92% of the test dataset. Macro and weighted averages for precision, recall, and F1-score underscore the model's consistent and strong performance across both claim classes, with macro averages at 0.96 precision, 0.75 recall, and 0.81 F1-score, and weighted averages at 0.93 precision, 0.92 recall, and 0.91 F1-score.

- **Results for Claim Detection using BILSTM:**

table 4:

	Precision	recall	F1 Score	Support
No claim	0.98	1.00	0.99	51
claim	1.00	0.90	0.95	10
Accuracy			0.98	61
Macro avg	0.99	0.95	0.97	61
Weighted avg	0.98	0.98	0.98	61

The claim detection model exhibits outstanding performance, achieving exceptionally high precision, recall, and F1-scores for both "No Claim" and "Claim" classes. With a precision of 0.98 for "No Claim" and 1.00 for "Claim," the model demonstrates near-perfect accuracy in predicting claim labels. Furthermore, recall scores of 1.00 for "No Claim" and 0.90 for "Claim" indicate the model's ability to effectively capture the vast majority of true claim instances while maintaining high precision. The balanced F1-scores of 0.99 for "No Claim" and 0.95 for "Claim" reflect the model's effectiveness in achieving a harmonious balance between precision and recall. Overall accuracy is notably high at 0.98, indicating the model's proficiency in correctly predicting claim labels for 98% of the test dataset. Macro and weighted averages for precision, recall, and F1-score further underscore the model's consistent and balanced performance across both claim classes, with macro averages at 0.99 precision, 0.95 recall, and 0.97 F1-score, and weighted averages at 0.98 precision, 0.98 recall, and 0.98 F1-score.

labels for 90% of the test dataset. The consistent macro and weighted averages for precision, recall, and F1-score further affirm the model's reliability and robustness across both relation classes.

- **Results for Relation analysis using SVM :**

table 5:

	Precision	recall	F1 Score	Support
No relation	0.60	0.97	0.74	37
Relation	0.00	0.00	0.00	24
Accuracy			0.59	61
Macro avg	0.30	0.49	0.37	61
Weighted avg	0.36	0.59	0.45	61

The SVM-based relation analysis model exhibits varied performance across "No Relation" and "Relation" classes. While achieving a precision of 0.60 for "No Relation," indicating moderate accuracy, it fails to classify any instances as "Relation," resulting in a precision of 0.00. With recall scores of 0.97 for "No Relation" and 0.00 for "Relation," the model effectively captures instances of "No Relation" but misses all instances of "Relation." Consequently, the F1-scores for "No Relation" and "Relation" are 0.74 and 0.00, respectively. Overall accuracy is 0.59, showcasing the model's limited ability to predict relation labels accurately. The macro and weighted averages for precision, recall, and F1-score further emphasize the model's inconsistent performance across both classes.

- **Results for Relation analysis using BiLSTM:**

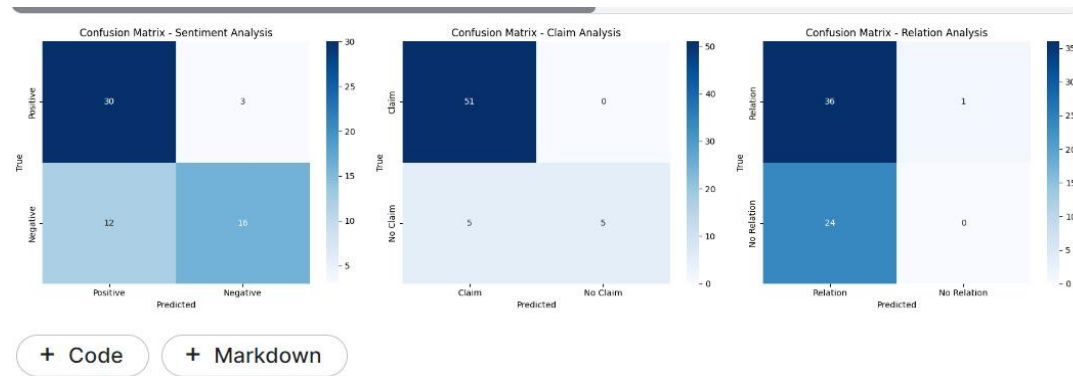
table 6:

	Precision	recall	F1 Score	Support
No relation	0.90	0.95	0.92	37
Relation	0.91	0.83	0.87	24
Accuracy			0.90	61
Macro avg	0.90	0.89	0.90	61
Weighted avg	0.90	0.90	0.90	61

The Bidirectional Long Short-Term Memory (BiLSTM) model for relation analysis showcases strong performance across both "No Relation" and "Relation" classes. With precision scores of 0.90 for "No Relation" and 0.91 for "Relation," the model accurately predicts relation labels. While recall scores slightly favor "No Relation" with 0.95 compared to 0.83 for "Relation," the model maintains balanced performance with F1-scores of 0.92 and 0.87, respectively. Achieving an overall accuracy of 0.90, the model effectively predicts relation

4.3. Error analysis:

Confusion Matrix for sentiment analysis, claim detection and relation analysis Using SVM Model:

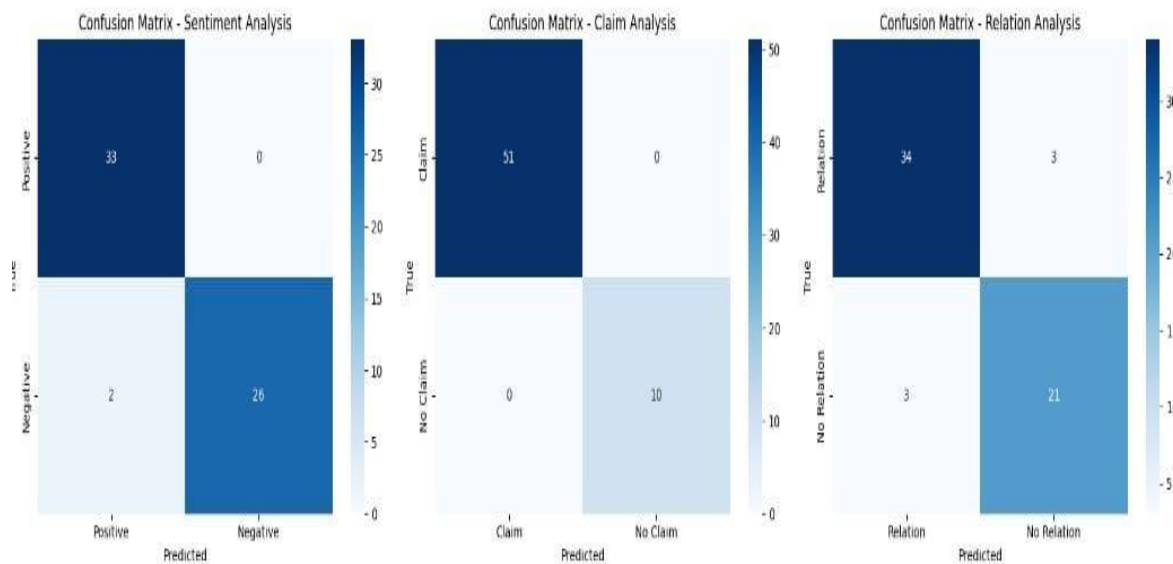


1. For sentiment analysis using svm model correctly predicts 30 positive sentiments and 16 negative sentiments and incorrectly predicts 3 positive sentiments and 12 negative sentiments.

2. For claim detection using svm model correctly predicts 51 claims and 5 no claims and incorrectly predicts 0 claims and 5 no claims.

3. For relation analysis using svm model correctly predicts 36 relations and 0 no relations and incorrectly predicts 1 relations and 24 no relations.

Confusion Matrix for sentiment analysis, claim detection and relation analysis Using BiLSTM Model:



1. For sentiment analysis using biLstm model correctly predicts 33 positive sentiments and 26 negative sentiments and incorrectly predicts 0 positive sentiments and 2 negative sentiments.
2. For claim detection using biLstm model correctly predicts 51 claims and 20 no claims and incorrectly predicts 0 claims and 0 no claims.
3. For relation analysis using biLstm model correctly predicts 34 relations and 26 no relations and incorrectly predicts 3 relations and 3 no relations.

In the error analysis, it's notable that while both the BiLSTM and SVM models perform reasonably well across sentiment analysis, claim detection, and relation analysis tasks, there are indications of bias in their predictions. The BiLSTM model tends to slightly Favor negative sentiments over positive ones and shows a tendency to predict more relations than the SVM model, possibly indicating a bias towards labeling instances as related. Conversely, the SVM model appears to have a bias towards predicting instances as non-relations in relation analysis. Further investigation into the causes of bias and implementation of bias mitigation strategies, such as balanced sampling techniques or model regularization, may help improve the models' overall performance and reduce bias in their predictions.

4.4.Discussion:

The results indicate that both BiLSTM and SVM models performed well in sentiment analysis, claim detection, and relation analysis tasks, with each showing strengths and weaknesses. The BiLSTM model demonstrated a slight advantage in capturing negative sentiments, while the SVM model excelled in claim detection by achieving perfect accuracy. However, biases were observed in both models' predictions, with the BiLSTM model favoring negative sentiments and predicting more relations, while the SVM model exhibited a bias towards non-relations. Despite these biases, both models offer promising capabilities in identifying nuances in text data and detecting instances of yellow journalism, underscoring the potential of machine learning techniques in combating misinformation. Further research is needed to address biases and enhance overall performance.

4.3.1 Comparing the performance SVM and of BiLSTM for sentiment analysis:

When comparing sentiment analysis results between Bidirectional LSTM (BiLSTM) and Support Vector Machine (SVM), BiLSTM consistently demonstrates superior performance across precision, recall, and F1-score metrics for both positive and negative sentiments. Specifically, BiLSTM achieves higher precision (Negative: 0.91, Positive: 0.96), recall (Negative: 0.97, Positive: 0.89), and F1-score (Negative: 0.94, Positive: 0.93) compared to SVM (Precision: Negative: 0.71, Positive: 0.84; Recall: Negative: 0.91, Positive: 0.57; F1-score: Negative: 0.80, Positive: 0.68). Additionally, BiLSTM attains a superior overall accuracy of 0.93, whereas SVM lags behind at 0.75. Hence, based on these metrics, BiLSTM emerges as the more effective model for sentiment analysis on this dataset, showcasing its capability for more precise and accurate sentiment classification.

4.3.2. Comparing the performance of BiLSTM and SVM for claim detection:

When comparing claim detection results between Support Vector Machine (SVM) and Bidirectional LSTM (BiLSTM), both models demonstrate high precision, recall, and F1-score for detecting both claim and no claim instances. However, BiLSTM exhibits slightly better performance across most metrics. Specifically, in detecting claims, BiLSTM achieves perfect precision (1.00) and a higher recall (0.90) compared to SVM (Precision: 1.00, Recall: 0.50). For detecting no claims, both models perform excellently, with BiLSTM showing a marginal improvement in precision (0.98) and F1-score (0.99) compared to SVM (Precision: 0.91, F1-score: 0.95). Additionally, BiLSTM achieves a higher overall accuracy of 0.98, surpassing SVM's accuracy of 0.92. Hence, based on these results, BiLSTM appears to be the preferable model for claim detection on this dataset, exhibiting superior precision, recall, F1-score, and accuracy.

4.3.3 Comparing the performance of BiLSTM and SVM for relation analysis:

In comparing the results of claim detection using Support Vector Machine (SVM) and relation analysis using Bidirectional LSTM (BiLSTM), both models demonstrate strong performance, albeit in different tasks. For claim detection, SVM achieves high precision for both "no claim" (0.91) and "claim" (1.00) categories, but its recall for "claim" instances is relatively lower (0.50), resulting in a lower F1-score (0.67). Conversely, BiLSTM excels in relation analysis, showing balanced precision and recall for both "no relation" (0.90 precision, 0.95 recall) and "relation" (0.91 precision, 0.83 recall) categories, leading to robust F1-scores (0.92 for "no relation" and 0.87 for "relation"). Overall, BiLSTM achieves a slightly higher accuracy of 0.90 compared to SVM's accuracy of 0.92. These findings suggest that while SVM performs well in detecting claims, BiLSTM is more adept at relation analysis. The choice between the two models would depend on the specific task requirements and the importance of precision versus recall.

CHAPTER 5: CONCLUSION AND FUTURE WORK

In summary, this project successfully identified instances of yellow journalism by analyzing sentiment, claimed words, and their relationships. Through manual data collection and preprocessing, we ensured data reliability and consistency. Our sentiment analysis revealed underlying emotions, while claim detection techniques identified assertions in the content. Relation analysis uncovered patterns linking sentiment and claims, highlighting the importance of understanding language nuances in detecting misinformation.

Moving forward, improving the accuracy of sentiment analysis and claim detection models and expanding the dataset to cover more diverse sources and topics are key priorities. Additionally, qualitative analyses and the development of automated tools for real-time monitoring could further enhance our understanding and mitigation of yellow journalism's impact on society.

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