SENTIMENT ANALYSIS OF NEWS ARTICLES USING BIDIRECTIONAL RECURRENT NEURAL NETWORKS

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Methodology

Methodological Framework

A research methodological framework allows a researcher to illustrate the core steps in conducting a research and helps the reader to understand the given steps the researcher took to receive their end results. This aids in replication of the research and helps identify potential criticisms of the research. This thesis will follow four main steps.

1. Research Gap Identification
2. Data Collection
3. Data Preprocessing
4. Exploratory Data Analysis
5. Model Construction
6. Model Performance Evaluation
7. Model deployment

Through literature review, research gaps are found and the purpose of this study is constructed. We determined that this research will encounter the following challenges in it's methodology:

1. Determining the correct dataset and ensuring that the proper features are extracted from the data prior to model training.
2. Choosing the correct model and training method. Which can greatly impact the final behaviour of the model and the results of this research. If training is supervised or semi-supervised, then the data labelling method must be considered too.
3. Choosing a dataset to analyse relationships between politics opinions and emotional sentiment.

4. Determining the proper visualizations such that relationships between data are made clear.

Data Collection

The subject of this study is long-form text in the form of news articles, therefore the data used has to be same. Most articles are freely available on internet and are often scraped by users on the net and published through Kaggle and Mendeley Data or on independent websites. The main obstacle to data collection is the diversity and size of the new article dataset. Preferably, the project requires a large dataset of atleast 1 million articles and sufficient diversity of data such that all kinds of news outlets are covered regardless of bias and regardless of the factuality of it's contents. This makes the All The News 2.0 Dataset (Thompson, n.d.) suitable for analysis. All the News 2.0 is a large dataset containing 2.6 million articles from news of different websites including author, title, main text and publication. The size and diversity makes it perfect for use in analysis of news media.

Model and training Choice

Prior to model construction, it is important to both chose the model and chose the training method that is being used for research. For this research, BiLSTM is chosen as it has been proven in the literature review to have promising results in sentiment analysis. BiGRU is similar and offers slightly lower performances but is more lightweight and would also be chosen alongside BiLSTM to compare performances. The bidirectionality of these models provide them the capability to analyse sentences in context of the sentences before and after and has been proven in Literature Review to have great results in sentiment analysis for shorter forms of text.

The type of model greatly determines the methods of data preprocessing and how much of the data is labelled. For most of previous sentiment analysis research, supervised analysis is used. (Wankhade et al., 2022) noted that semi-supervised

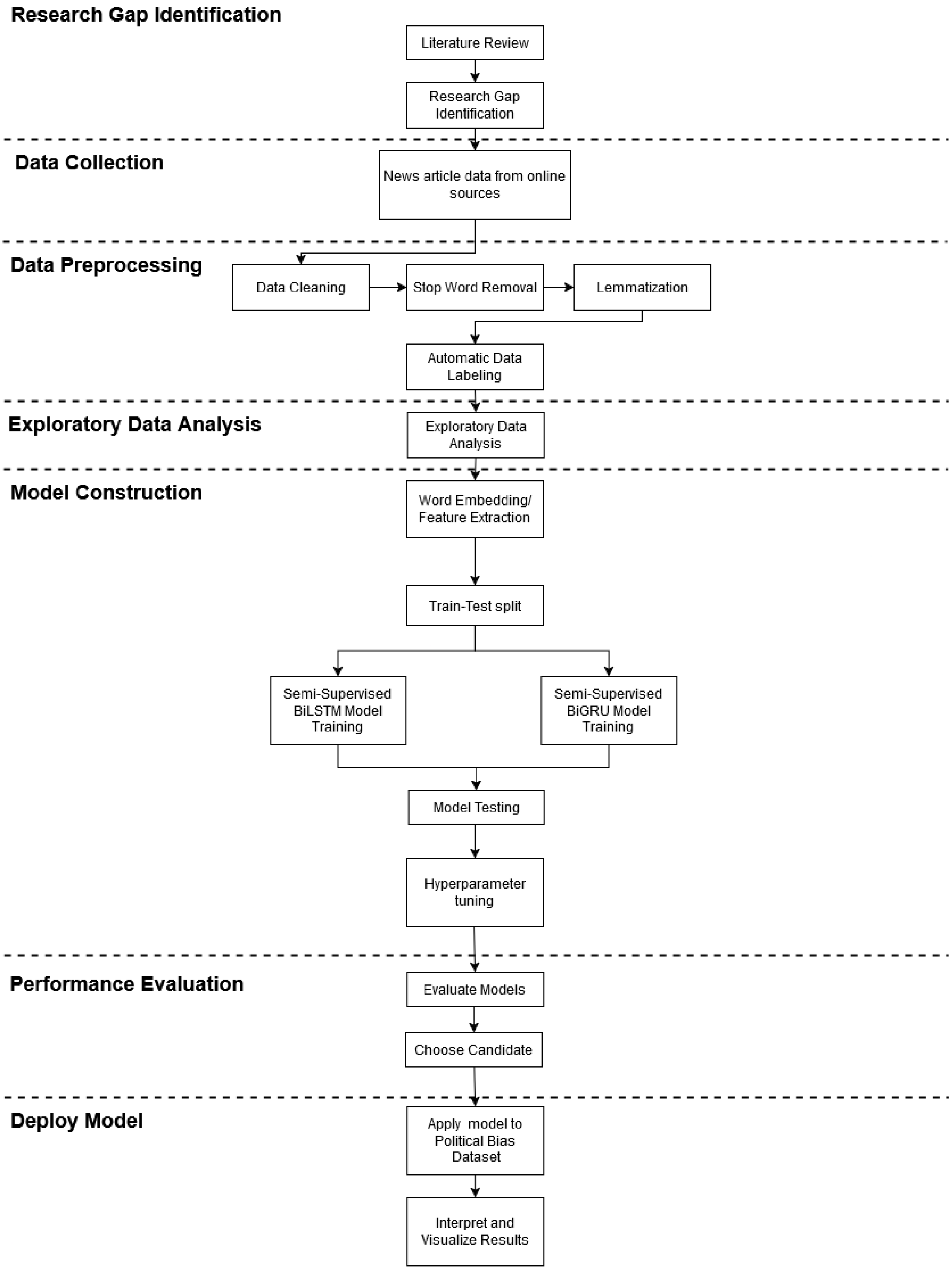

Research Gap Identification
Literature Review
Research Gap Identification
Data Collection
News article data from online sources
Data Preprocessing
Data Cleaning
Stop Word Removal
Lemmatization
Automatic Data Labeling
Exploratory Data Analysis
Exploratory Data Analysis
Model Construction
Word Embedding/ Feature Extraction
Train-Test split
Semi-Supervised BiLSTM Model Training
Semi-Supervised BiGRU Model Training
Model Testing
Hyperparameter tuning
Performance Evaluation
Evaluate Models
Choose Candidate
Deploy Model
Apply model to Political Bias Dataset
Interpret and Visualize Results

Figure 1 Illustration of the research framework

training may be more effective at handling ambiguity (such as an ambiguous sentiment score) while supervised training is better at handling subjectivity. Since most of the data will contain objective use of language, large amounts of subjective language is not of concern. Ultimately, semi-supervised training will be used as to account for more equivocal sentences and sentiment that is harder to evaluate under supervised training.

Data Preprocessing

Data Preprocessing for text involves feature extraction so that the accuracy of the model is increased and sentiment labelling in order to direct the model into doing sentiment analysis.

Data Cleaning

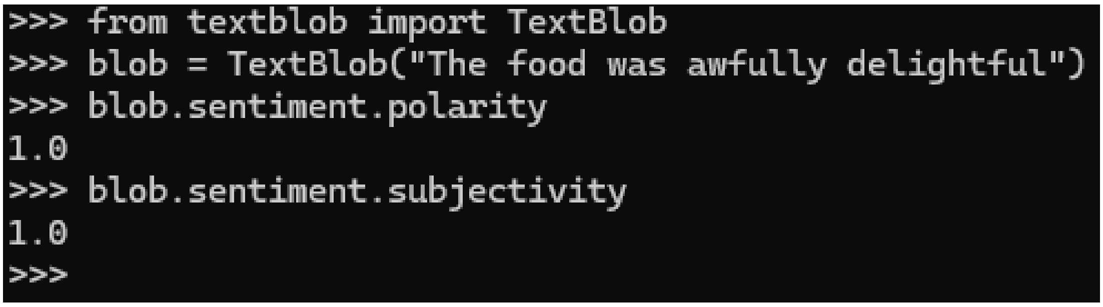
Prior to preprocessing the data, we must ensure that the training/testing data does not contain any irrelevant noise that may decrease the accuracy of the model. For this research, the model must properly interpret professional English journalism and so flaws that may impede this process are:

1. Hyperlinks (https:// or http://)
2. Stop words (a,the,in)
3. Punctuations (, . @ !)
4. Unusually capitalized words/ lowercase words (sUCh aS THIS)
5. Non-Ascii Characters
6. Word contractions (-’s, -’re, -’d)
7. Duplicated words

In addition, missing values, invalid values (such as a text being too short), satirical articles (such as The Onion and The Babylon Bee) and tabloids/pop culture magazines (TMZ, The Sun,...) are removed. Words that are not the root of a word should then be lemmatized (eg. Happily becomes happy, mournful becomes mourn). To prepare the data for word embedding and sentiment labelling, the data will then be split into individual sentences.

Data Labelling

For the training/testing dataset, the data is labelled as to prepare for supervised training using automatic labelling software. This project will utilize TextBlob, a library for text mining and NLP, it utilizes a rule-based approach to labelling individual sentences. Compared to competitors like SentiWordNet 3.0 and VADER, TextBlob is able to output emotional polarity scores and sentence objectivity scores while simultaneously handling the context of surrounding words. During exploratory data analysis, all of the data will be labelled and utilized for a rules based analysis of the corpus. However, training will be semi-supervised and a majority of the labelled data will be obscured so as to facilitate the pseudo-labelling during training.



```
>>> from textblob import TextBlob
>>> blob = TextBlob("The food was awfully delightful")
>>> blob.sentiment.polarity
1.0
>>> blob.sentiment.subjectivity
1.0
>>>
```

Figure 2 Demonstration of TextBlob’s sentiment labelling. TextBlob is able to probably handle the phrase ”awfully delightful” and accurately output a positive score for polarity and subjectivity.

Word Embedding

The main methods of transforming words into vectors are documented within the literature review. Between the three options, Word2Vec is preferable as to avoid potential computational constraints that may be met when running GloVe. Word2Vec is comparably lightweight compared to GloVe while still extracting features based on context.

The vectors from the result of Word Embedding will then be normalized with min-max scaling as to ensure that data is standard and uniform while maintaining the relationships between vectors. Because Word2Vec is an unsupervised clustering model like K-means, it is difficult to evaluate it's accuracy.

Model Training and Data Split

The data will be split between Training, Testing and Validation on a 80/10/10% split. Training data is used to help the model learn and encode patterns within data, the testing data is used to evaluate the performance of the model and the validation set is used to tune hyper-parameters of the model. Within semi-supervised training, only a small part of the training data is labelled while the rest is pseudolabeled. Pseudolabelling is the process of labelling unlabelled training data and then adding it back to the training data on the next session. Only 10% of the training data will labelled this way and the remaining are pseudolabelled.

When a model is done training, it moves to the hyper-parameter tuning section of the phase where the validation set is used to adjust variables like learning rate and optimiser momentum. After which, it loops back to training until gradient change of the loss function is too little for any noticeable improvement.

As noted in model choice, the models used for this research will be BiLSTM and BiGRU. The two will be trained simultaneously and at evaluation, the better performing model will be chosen to be deployed.

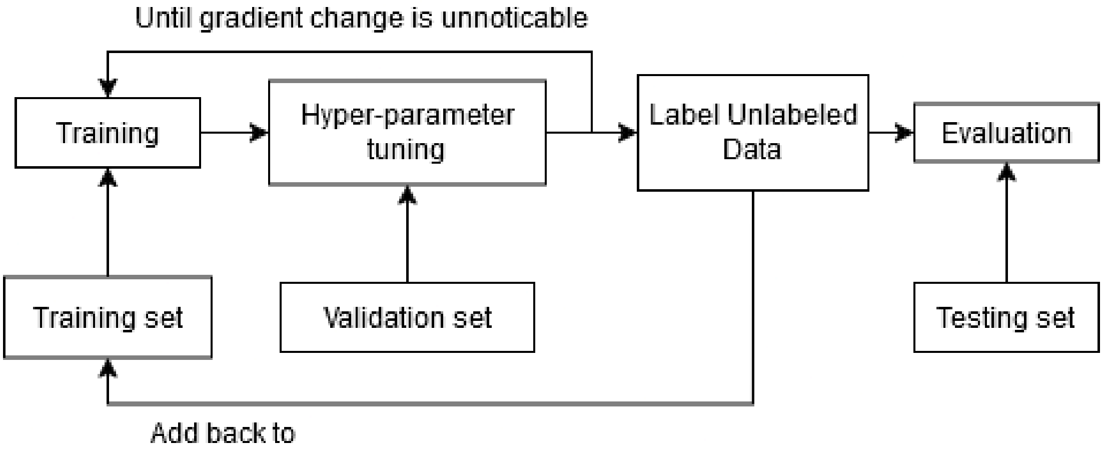


Figure 3   Semi-supervised training and evaluation process

Evaluation

The end model will be a classification model. A classification model labels data between two or more categories. Classification models are often evaluated using a confusion matrix which measures the amount of labels that were predicted correctly and incorrectly. The confusion matrix lists down the true positive (top left), false positive (top right), false negatives (bottom left) and true negatives (bottom right). Subsequent evaluation metrics like Recall, Precision, Accuracy and F1 score is derived from the initial confusion matrix. Due to the research's use of SentiWordNet, the confusion matrix used is 3x3 to evaluate positive, negative and neutral responses.

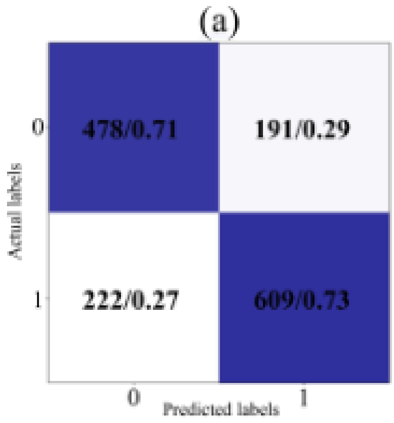
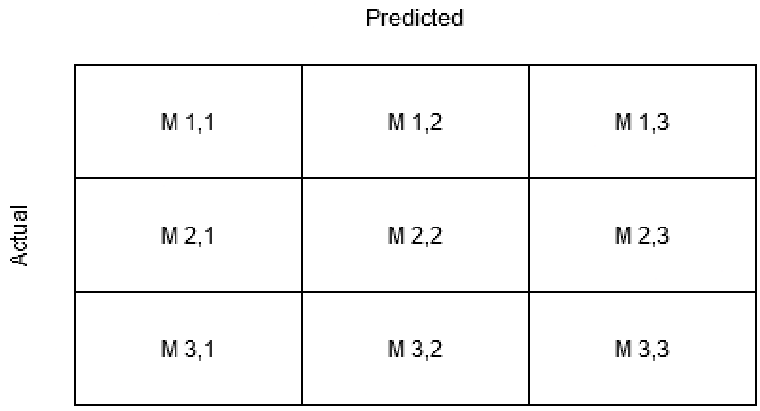


Figure 4   Example of a Confusion matrix(Mu et al., 2024)

Below are the formulae for Accuracy, Precision, Recall and F1 scores respectively within a nxn confusion matrix M for a given element α and given that columns are predicted values and rows are actual values. The diagonals are true positives and every other element is a mismatch.



	Predicted		
	M 1,1	M 1,2	M 1,3
Actual	M 2,1	M 2,2	M 2,3
	M 3,1	M 3,2	M 3,3

Figure 5 Reference for 3x3 confusion matrix

$$\begin{align}
\text{Accuracy} &= \frac{\sum_{i=0}^{n} M_{i,i}}{n} \tag{1}\\
\text{Precision}_\alpha &= \frac{M_{\alpha,\alpha}}{\sum_{i=0}^{n} M_{i,\alpha}} \tag{2}\\
\text{Recall}_\alpha &= \frac{M_{\alpha,\alpha}}{\sum_{i=0}^{n} M_{\alpha,i}} \tag{3}\\
\text{F1}_\alpha &= \frac{2\text{Precision}_\alpha\text{Recall}_\alpha}{\text{Precision}_\alpha + \text{Recall}_\alpha} \tag{4}\\
&\tag{5}
\end{align}$$

Accuracy is the general measurement of the model's ability to label text correctly. Precision of a given label is the amount of data that are correctly classified, recall of a given label is the amount of points classified under that classification. F1 is the mean of both precision and recall.

Model Deployment and Visualization

After the model is evaluated, the model is used for analysis for polarity within the analysis dataset (All The News 2.0) in order to measure the polarity of articles within various news publications. Prior to deployment, the dataset must also be cleaned in a similar manner to the data cleaning section as to ensure accurate results. The dataset is also labelled via AllSides (*AllSides*, n.d.) in order to categorize them by media bias labels ranging from far left to far right. The resulting statistics will be noted and published in the form of various graphs such as a scatter plot or bar chart which is frequently used for visualizing multiple dimensions of data at once. These visualizations will be made using matplotlib and the results of the analysis will be meticulously interpreted.

References

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Mu, G., Li, J., Li, X., Chen, C., Ju, X., & Dai, J. (2024). An Enhanced IDBO-CNN-BiLSTM Model for Sentiment Analysis of Natural Disaster Tweets. *Biomimetics*, *9*(9). (Publisher: Multidisciplinary Digital Publishing Institute (MDPI))

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