Fake News Detection

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Group 12
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Abstract

Unreliable news has become a critical societal issue given the prevalence of digital media in today's society, as veracity can be difficult to determine even by human inspection, regardless of media literacy. In this paper, we build a classifier which distinguishes between four different news types: satire, hoax, propaganda and reliable news. The baseline model for this classification task is Multinomial Naive Bayes, with the TF-IDF vector as input. To improve upon this, we incorporate linguistic and semantic features, and utilise sentence embeddings from transformers, specifically the Bidirectional Encoder Representations from Transformers (BERT). We have developed a lightweight solution that is performant in detecting fake news. Secondly, we identify key features of unreliable news to elucidate a better decision-making process when considering the trustworthiness of news articles.

1. Introduction:

Recent years have seen a rise in the prevalence of fake news, especially in the social media era. With the increased ease of sharing information online through various platforms other than credible news sources, it is becoming challenging to differentiate between reliable articles and fake news. This leads to potentially harmful consequences for both individuals and society as a whole.

The veracity of unreliable news can be difficult to determine even by human inspection regardless of media literacy. It is even harder as many unreliable news articles try to emulate reliable news articles to enhance their persuasiveness (Baptista & Gradim, 2020). Based on a survey, while 79% of Singaporeans are somewhat confident in their ability to detect fake news, 91% incorrectly identified at least one piece of unreliable news as being reliable. (Soon & Goh, 2018).

As there is misplaced complacency in detecting unreliable news, (Soon & Goh, 2018), the aim of this paper is to develop a classifier that can detect unreliable news to be used to implement a system in place to warn readers of possible unreliable news before reading it.

Given a news article, our model will classify it into one of the four labels. The labels are defined (Zimbars, 2016) as:

Satire: Articles that use humour, irony, exaggeration, ridicule, sarcasm to comment on current events. Readers are expected to know that it is not meant to be taken seriously.
Hoax: Articles that entirely fabricate information, disseminate deceptive content, or grossly distort actual news reports that are spread *regardless of an intent to mislead*.
Propaganda: Articles that come from a particular point of view that may contain false claims, information and conspiracy theories that are spread *with the intent to mislead*.
Reliable news: Articles that circulate news and information in a manner consistent with traditional and ethical practices in journalism.

If readers are informed beforehand that the information could be unreliable, they would process it differently while reading the article as they are less likely to believe the article (Ecker et al., 2010). While not able to eliminate it altogether, specific warnings about misinformation before articles would reduce the continued influence of misinformation (Grady, Ditto & Loftus, 2021). By further identifying the specific type of unreliable news, we hope to equip readers with a more perceptive lens of the motives of each text and help them read with more discretion.

In this paper, we implement a model that uses various linguistic and semantic features, combined with transformers, specifically the Bidirectional

Encoder Representations from Transformers (BERT) Model to classify the articles into the four labels. Doing so would give us a better understanding of the features that readers should look out for in fake news. The system that can be implemented with the model has the potential to reduce the spread of misinformation and fake news in today's society.

2. Related Work:

The problem of fake news detection has received significant attention in recent years with various methods to develop effective solutions. In Zhan et al., 2022, linguistic features of COVID-19 articles were analysed for a 2-way classification (reliable and unreliable). The authors found patterns, such as reliable news having higher proportion of neutral sentiments and being easier to read with different lexical categories and keywords. However, as the text corpus focused on COVID-19 related texts, the model's generalizability may be limited to that particular context.

Biyani et al. (2016) analysed the properties of clickbait and non-clickbait articles. The paper offers various syntactic features targeted at identifying clickbait headlines and body text. Our project adapts these features as the same features are typically found in hoax and propaganda as w made to look more interesting to lure clicks.

Rashkin et al. (2017) analyses the linguistic characteristics of fake news articles and shows that through incorporating sentiment analysis and language pattern analysis in our model, the reliability of news can be predicted.

Blanke & Venturini (2021) explores a network view on the complex politics of association involved in the reliability of news sites and relies on features derived from graph theory for its prediction. However, it works with a highly curated dataset, which is smaller in size, and focuses less on scale and accuracy, especially with borderline sites.

Hu et al. (2021) proposes an alternative solution that implements an external knowledge base for fact checking purposes. However, the knowledge base has to constantly be updated or the fact checker will not be able to generalise well. As this would take up too much resources, our project aims to develop a light-weight solution as opposed to a full-scale hierarchical encoding framework proposed in the paper.

Our project aims to expand on prior works and look into linguistic features, specifically the analysis of syntactic and semantic features, on articles of a broader scope and expand it to the context of a 4-way classifier. Our project also utilises a relatively large and less curated dataset converse to Blank & Venturini.

3. Corpus Analysis & Method:

The dataset used is obtained from Hu et al. (2021) In the 'fulltrain.csv' file, there are a total of 48854 data points, distributed into different classes as shown:

Class	**No. of samples**	**% of total**
1 - Satire	14047	28.75
2 - Hoax	6942	14.21
3 - Propaganda	17870	36.58
4 - Trusted	9995	10.46

Table 1: Distribution of classes in dataset

Each sample is a document in English, sourced from news websites, with ranging length from as short as 2 words to paragraphs as long as 7152 sentences (117,495 words). The wide variations in data points can potentially result in difficulties modelling the classification.

We note other complications in the corpus: many documents contain Unicode symbols, web links or ads. Additionally, as text from one website may be split into many data points, some data points may be closely correlated to each other, such as having the same subject of discussion. Some samples contain headlines prepended to the news article, while others do not contain headlines.

Word Cloud

To get a better understanding of the articles in the dataset, we plot word clouds for each label.

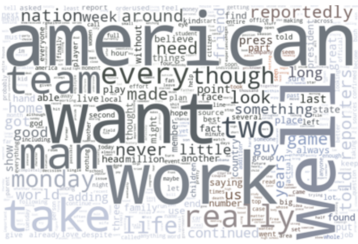

Fig 1. Word Cloud for articles labelled 'Satire'

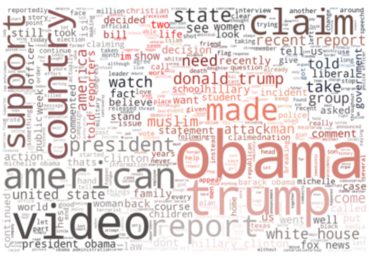

Fig 2. Word Cloud for articles labelled 'Hoax'

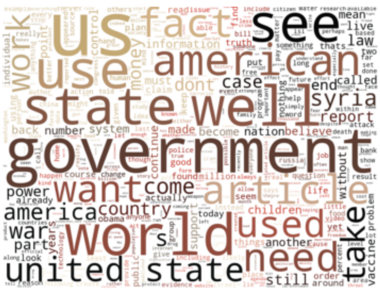

Fig 3. Word Cloud for articles labelled 'Propaganda'

Fig 4. Word Cloud for articles labelled 'Reliable News'

The word clouds give insight into the keywords and topics for each class of articles. For example, while the topics of hoaxes and propaganda both centre on politics, hoaxes tend to bring in specific political figures like Trump and Obama as shown in Fig 2.

Furthermore, reliable news articles span a broader scope of topics with a more even distribution as shown in Fig 4. We used these insights in the feature engineering process and this translated into features such as the number of proper nouns and analysing the lexical categories of articles.

Data Preprocessing

We use the nltk library to remove special characters and stopwords, tokenize and lemmatize the text. We also derive POS tags with nltk.

Additionally, we experimented with the use of extractive text summarization as a preprocessing step for the classification task, with the motivation being the large differences in writing styles of news articles depending on the source. Text summarization would serve as a means of obtaining the main content of the text, omitting any unimportant information and potentially reducing the idiosyncratic differences between texts written by different authors.

Syntactic Features

The syntactic features engineered are listed below, with a full table and rationale in Appendix A.

- Word count
- Sentence count
- First, second, third person pronouns
- Proper nouns
- Conjunctions
- Superlatives
- Hedging words
- Boosting words
- Numbers
- Number of consecutive all capitalised words

Semantic Features

In this section, we delve into the linguistic and semantic characteristics of satire, hoaxes, propaganda and reliable news and experiment with these characteristics to build a model.

Semantic features are aspects of the meaning of a text, such as its topics, sentiment, and context. These features can be extracted using natural language processing (NLP) techniques, such as word embeddings, topic modelling, and sentiment analysis. Analysing the semantic features of a text can help us gain insights into its meaning and identify patterns that are indicative of the type of argument.

Class	Characteristics
Satire	Sarcasm, irony, hyperbole, exaggeration, understatement and allegory. (MasterClass, 2021)
Hoax	Vagueness, detail, imaginative writing, deception, humour, complexity, and lack of formality. (Baron & Dearden, 2019)
Propaganda	Activates strong emotion and appeals to the hopes, fears, and dreams of a targeted audience. (Irfan, 2019)
Reliable News	Less reported speech, passive voice, negation, conjunctions, to-infinitive attributes, and more comparatives in reliable articles. Less hedging and vague words; more first-person, second-person pronouns, quotes and superlatives in unreliable articles. (Mahyoob et. al, 2020)

Table 2: Linguistic characteristics of each class

For instance, a propagandistic article about a political candidate may use overly emotional language to stir up readers' feelings rather than providing factual information (Irfan, 2019). Similarly, a fake news article may use certain topics or keywords that are commonly associated with fake news, such as conspiracy theories or sensational events (Baron & Deardon, 2019). By analysing the sentiments and objectivity of the article, we can detect these patterns and flag them.

We used the following semantic features:

- Sentiment Analysis
- Context Incongruity
- Lexical Categories

For sentiment analysis, we experimented with different libraries TextBlob and VADER.

A key identifier of satire, sarcasm, can be detected by context incongruities, which is defined by a mismatch between the sentiment polarities of words or phrases used in a sentence (Joshi et al., 2015). For example, ‘I love being ignored’ has a positive word ‘love’ and a negative word ‘ignored’. Thus, we calculated the number of consecutive n-grams with opposite polarity as a representation for these context incongruities.

Finally, we utilise Empath-Client (Fast, 2016) for analysing text across lexical categories. Based on our research into linguistic features of each class, we also generated new lexical categories to use for our analysis.

<u>Evaluation metric</u>

The proposed evaluation metric is the F1 score. It places equal emphasis on precision and recall and is able to succinctly summarise the performance of the model. A high F1 score would result from a high precision score and a high recall score, and both are important in the context of this study. We want to keep recall high because we would not want reliable, possibly important news to be wrongly classified as unreliable. At the same time, we want precision to be as high as possible to minimise unreliable articles from being falsely labelled as reliable, which can give false credibility to unreliable news, which can have catastrophic results.

4. Experiments:

In this section, we describe the different experiments we carried out with the aim of optimising a reliable news detection model. We explore the TF-IDF vectorizer, sentence encoding from BERT and various linguistic features. For the model, we compare a simple machine learning algorithm, the Naive Bayes algorithm, and a deep learning algorithm, neural networks. Additionally, we also experiment with a sentence summarizer to see how it would affect performance of the model.

Due to computational limitations, we took a sample of size 10,000 from the full dataset and trained the model on this sample with the syntactic and semantic features. We went on to test the model on a balanced test dataset.

By experimenting with a combination of different techniques and models, we aimed to identify the most effective combination for identifying fake news articles and develop a robust model that could label the news articles with high accuracy. We outline the specifics of our methodology and the findings in the sections that follow.

Baseline Model

For our baseline model, we chose a Naive Bayes model with TF-IDF sentence vectorization. Naive Bayes is a simple yet effective machine algorithm that works well with text classification tasks while TF-IDF is a simple and commonly used technique for vectorizing text in NLP tasks. Using TF-IDF to vectorize the sentence inputs from the text data and training a Naive Bayes classifier on the inputs, we obtain the following result:

Micro	**Macro**		
F1	Precision	Recall	F1
0.31	0.72	0.32	0.22

Table 3: Baseline Model Result

Our model uses the TF-IDF vector as input, using only terms with document frequency less than 0.7 (empirically determined). The limit on document frequency helps to filter out overly common words in the news articles that would otherwise add an element of similarity across all documents, helping to improve the discriminative power of the model by placing greater emphasis on more informative terms.

This baseline model helped us establish a starting point for our more intricate models and techniques – serving as a benchmark for comparison for our future experimentations.

Text Summarizer

A feature that we experimented with was the use of a sentence summarizer to preprocess text before feeding it into our models. Our hypothesis for utilising a summarizer was to shorten and reduce the complexity of the input so that our model could better extract features for classification, as well as reduce the input size for the model.

However, we found that the performance of our models decreased. This could be because the summarizer removed important details and nuances from the text, making it more challenging for the models to classify the text. Therefore, we conclude that including a summarizer in our pipeline is ineffective in improving the performance of our model.

Machine Learning Algorithm

We chose to use the Naive Bayes and neural network as our primary machine learning algorithms. Due to its simplicity, efficiency, highly scalability and ability to handle large datasets, Multinomial Naive Bayes, a widely used algorithm for text classification, was chosen. However, it has the assumption that each feature is independent of all others, which is not often true in NLP data, but it frequently works well in practice. Neural networks, on the other hand, are more complex models that use multiple layers of neurons to learn intricate patterns and links in the data. This makes them more powerful models compared to Naive Bayes. However, neural networks are often more computationally expensive and have decreased interpretability. Nevertheless, neural networks have shown great performance and robustness in a variety of NLP tasks, and we use them as a basis of comparison

With these 2 machine learning algorithms, we permuted them with the different linguistic features that we had came up with to get the results in the following table:

Mode	Input	Micro[1]	Macro		
		F1	Precision	Recall	F1
NB	TF-IDF	0.318	0.72	0.32	0.22
	Syntactic features	0.433	0.47	0.43	0.44
	TF-IDF + syntactic features	0.300	0.69	0.30	0.20
	TF-IDF + sentiment (TextBlob)	0.555	0.67	0.55	0.51
	TF-IDF + sentiment (VADER)	0.554	0.66	0.55	0.51
	TF-IDF + Context Incongruity	0.554	0.67	0.55	0.51
	TF-IDF + lexical categories	0.555	0.67	0.55	0.51
	All above features (w/o vectorizer)	0.361	0.46	0.35	0.28
NN	BERT	0.542	0.544	0.550	0.539
	BERT + syntactic features	0.633	0.635	0.633	0.634
	BERT + sentiment (TextBlob)	0.632	0.628	0.632	0.603
	BERT + sentiment (VADER)	0.626	0.626	0.626	0.593
	BERT + Context Incongruity	0.618	0.608	0.618	0.585
	BERT + lexical categories	0.634	0.660	0.634	0.610
	All above features (w/o BERT)	0.492	0.514	0.492	0.478
	All above features (w/ BERT)	**0.641**	**0.653**	**0.663**	**0.650**

Table 4: Experiment Results

[1] Only Micro F1 is reported since Micro F1=Micro Precision=Micro Recall.

Our results show that BERT-based models perform the best. On average, the BERT-based models achieve a higher F1 score of approximately 0.60 for most tests.

Models that incorporate TF-IDF as vectorial representation of the sentences instead of using BERT sentence encoding was comparatively weaker, with a lower F1 score. This suggests that improving the sentence vectorizer would lead to much better performance rather than specific linguistic features.

Our results also show that using a more robust model such as a Neural Network is able to achieve higher performance for this particular classification task, which can be seen when comparing the results for the features without sentence embedding for both models. However, with the Naive Bayes model having lower performance, we are better able to compare the impact and contribution of the linguistic features to the model's ability to classify the news article.

Overall, syntactic features improved the model's performance in most metrics, except for precision. Combining that with TF-IDF did not help improve the model's performance. It is also worth noting that TF-IDF is able to achieve a high macro precision but a much lower recall and F1 score.

Semantic features have shown to be useful for reliable news detection, as they capture the meaning of a text rather than its surface-level properties.

For sentiment analysis, we compare TextBlob with its alternative VADER. TextBlob performed marginally better on our dataset than its counterpart. This can be attributed to the fact that VADER focuses on identifying the sentiments of content that typically appear on social media, such as emojis, repetitive words, and punctuation. Since our use case was for news text, TextBlob was slightly more appropriate and showed better results in our metrics.

Training the model with n-gram of lengths 1 to 5 to detect context incongruity also produced similar results in terms of the different metrics.

Training the model with each of the lexicons separately helped us see the effects of each lexicon on the model. We picked the lexicons with the best performance for the final model.

Testing using samples from the training set

We compare the model's performance when a 80/20 train/test split from the full train dataset is used instead of the balanced test dataset. Our TF-IDF Naive Bayes model had an F1 score of 0.638 while the BERT Neural Network model had an F1 score of 0.982.

When testing with samples from the train set, we observe better performance, since our training and test datasets were from different news sources (Vaibhav, 2019). While training on one dataset and testing with a completely different dataset might seem like an unfair test at first glance, this is a good reflection of how our model is intended to be used (i.e. training on some dataset and testing on completely new data from new sources). It is likely that different news publications have different writing styles. Thus, we opted to use the `balancedtest.csv` test dataset for the main part of our evaluation.

Secondly, we can see that the both models were overfitted to the dataset (especially the BERT Neural Network) and were able to perform well for news articles from a specific source, but did not generalise well when tested against news articles from a different source.

In an attempt to overcome the overfitting, we ran the models with only the extracted features, intentionally leaving out the actual news article. The intuition behind this is to allow the model to only focus on the extracted features without being overly reliant on some features that are unique to the training dataset.

Hence, while our evaluation scores for each model may be lower than if we evaluated against the training set, the depicted scores are more reflective of the models' performance in a real-world setting and we believe that our model still generalises to a reasonable extent.

5. Discussion:

1. Do syntactic or semantic features affect the reliability of a news article more?

Semantic features have shown to be useful for reliable news detection, as they capture the meaning of a text rather than its surface-level properties. However, it is important to note that semantic features should be used in conjunction with other techniques to achieve better results in reliable news detection.

2. Does text summarization serve well as a preprocessing step in the classification of news articles?

Our experiments showed that text summarization does not serve well as a preprocessing step. The original rationale for using extractive summarization is that it would preserve the content of the news articles while removing any differences injected by the different authors. The classifier model would then classify the articles based purely on content.

However, we found that this approach removes important syntactic and semantic features that are critical in distinguishing between reliable and unreliable news articles. For example, text summarization may remove important contextual information, such as named entities, that could help identify the source and veracity of the article.

From these experiments with text summarization, we draw the conclusion that content alone is not sufficient to perform the classification of new articles by their reliability.

To address these shortcomings, we attempted alternative preprocessing techniques that can preserve important features while reducing noise. For example, part-of-speech tagging and semantic analysis turned out to be more effective in preserving syntactic and semantic information.

3. Why does Neural Network outperform the Naive Bayes Model?

In comparison to the Naive Bayes model, the neural network model showed better performance in this task, where comparing the result for the 2 models for the linguistic features only, without sentence vectorizers, boasting an F1 Score of 0.492 for the neural network compared to 0.36 for Naive Bayes. The reason for this is that the neural network is able to capture more complex patterns and relationships within the data that may not be caught by simpler models such as the Naive Bayes.

The neural network can handle large, high-dimensional datasets and is more flexible at modelling non-linear decision boundaries over the Naive Bayes model. Furthermore, the neural network can learn features automatically from the data, reducing the need for manual feature engineering as it is able to learn features automatically from the data, some of which we might never think of ourselves. However, we can see that the linguistic features do contribute to the overall performance of the BERT neural network models and gives the model some explainability as opposed to the pure black box model nature of the neural network.

6. Conclusion:

In conclusion, we have developed a model that can accurately classify news articles into different categories. We have found out that combining semantic and syntactic features, and using neural networks with transformers are effective ways to construct a powerful model.

Moving forward, we believe that our model can be improved by training it on a larger dataset and implementing fact-checking using knowledge graphs. Furthermore, there are other areas where our model could be applied, such as in developing tools for media literacy or assessing the credibility of online information sources. Our findings suggest that machine learning approaches have the potential to mitigate the negative impact of fake news and contribute to a more informed society.

Limitations

The first concern is the potential for algorithmic bias, especially for the neural network implementation, where the model may exhibit unfair or discriminatory behaviours towards certain groups due to bias in the train data. The classification of the news articles could potentially have certain political or ideological implementations, leading to the model exhibiting bias towards certain stances.

Another possible limitation is that since the test and train data are conflated with each other in terms of their publishing dates, the model may not perform as well on new (fake) news stories.

Considering the research scope, being able to identify fake news would also mean that it can be used the other way: to write better fake news that can circumvent the model. Taking advantage of the list of features from feature engineering done for this model, malicious actors creating fake news can use it against our goal. Additionally, there is the possibility that our model could be used to spread misinformation or propaganda. It is hence important for readers to use the findings responsibly to promote accurate and trustworthy journalism.

References

Baptista, J. P., & Gradim, A. (2020). Understanding fake news consumption: A Review. *Social Sciences*, *9*(10), 185. https://doi.org/10.3390/socsci9100185

Baron, A., & Dearden, E. (2019). *Fool's errand: Looking at april fools hoaxes as disinformation through ...* Retrieved April 4, 2023, from https://eprints.lancs.ac.uk/id/eprint/132007/1/dearden.pdf

Biyani, P., Tsioutsiouliklis, K., & Blackmer, J. (2016). "8 amazing secrets for getting more clicks": Detecting clickbaits in news streams using article informality. *Proceedings of the AAAI Conference on Artificial Intelligence*, *30*(1). https://doi.org/10.1609/aaai.v30i1.9966

Blanke, T. and Venturini, T. (2021) "A network view on reliability: Using machine learning to understand how we assess news websites," *Journal of Computational Social Science*, 5(1), pp. 69–88. Available at: https://doi.org/10.1007/s42001-021-00116-w.

Ecker, U. K. H., Lewandowsky, S., & Tang, D. T. W. (2010). Explicit warnings reduce but do not eliminate the continued influence of misinformation. *Memory & Cognition*, 38(8), 1087–1100. https://doi.org/10.3758/mc.38.8.1087

Ethan Fast, Binbin Chen, and Michael S. Bernstein. 2016. Empath: Understanding Topic Signals in Large-Scale Text. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. Association for Computing Machinery, New York, NY, USA, 4647–4657. https://doi.org/10.1145/2858036.2858535

Grady, R., Ditto, P., & Loftus, E. (2021, December 1). Nevertheless, partisanship persisted: fake news warnings help briefly, but bias returns with time. *Cognitive Research: Principles and Implications*, Vol. 6, pp. 1–16.

Heylighen, F., and Dewaele, J.-M. (1999). Formality of language: definition, measurement and behavioral determinants. *Interner Bericht, Center Leo Apostel, Vrije Universiteit Bru ̈ssel.*

Hu, Linmei and Yang, Tianchi and Zhang, Luhao and Zhong, Wanjun and Tang, Duyu and Shi, Chuan and Duan, Nan and Zhou, Ming (2021) Compare to The Knowledge: Graph Neural Fake News Detection with External Knowledge. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 754–763. https://aclanthology.org/2021.acl-long.62/

Irfan, H. K. M. (2019). An analysis of the linguistic techniques of Propaganda in marketing and politics. *International Journal of English Learning & Teaching Skills*, *2*(2), 1181–1195. https://doi.org/10.15864/ijelts.2213

Joshi, A. A., Sharma, V., & Bhattacharyya, P. (2015). Harnessing Context Incongruity for Sarcasm Detection. *International Joint Conference on Natural Language Processing*. https://doi.org/10.3115/v1/p15-2124

Mahyoob, M., Algaraady, J., & Alrahaili, M. (2020). Linguistic-based detection of fake news in social media. *International Journal of English Linguistics*, 11(1), 99. https://doi.org/10.5539/ijel.v11n1p99

MasterClass. (2021). What is satire? how to use satire in literature, pop culture, and politics-plus tips on using satire in writing - 2023. What Is Satire? How to Use Satire in Literature, Pop Culture, and Politics—Plus Tips on Using Satire in Writing. Retrieved April 10, 2023, from https://www.masterclass.com/articles/what-is-satire-how-to-use-satire-in-literature-pop-culture-and-politics-plus-tips-on-using-satire-in-writing#4AtbA6Er30m4RdavHTGhG

Rashkin, H., Choi, E., Jang, J. Y., Volkova, S., & Choi, Y. (2017). Truth of varying shades: Analyzing language in fake news and political fact-checking. *Proceedings of the 2017*

Conference on Empirical Methods in Natural Language Processing. https://doi.org/10.18653/v1/d17-1317

Soon, C., & Goh, S. (2021). (rep.). SINGAPOREANS' SUSCEPTIBILITY TO FALSE INFORMATION. Singapore, Singapore: Institute of Policy Studies.

Vaibhav Vaibhav, Raghuram Mandyam, and Eduard Hovy (2019). Do Sentence Interactions Matter? Leveraging Sentence Level Representations for Fake News Classification. In *Proceedings of the Thirteenth Workshop on Graph-Based Methods for Natural Language Processing (TextGraphs-13)*, pages 134–139, Hong Kong. Association for Computational Linguistics. https://aclanthology.org/D19-5316/

Zhan, K. et al. (2022) "Data Exploration and classification of news article reliability: Deep Learning Study," *JMIR Infodemiology,* 2(2). Available at: https://doi.org/10.2196/38839.

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Statement of Independent Work

1A. Declaration of Original Work. By entering our Student IDs below, we certify that we completed our assignment independently of all others (except where sanctioned during in-class sessions), obeying the class policy outlined in the introductory lecture. In particular, we are allowed to discuss the problems and solutions in this assignment, but have waited at least 30 minutes by doing other activities unrelated to class before attempting to complete or modify our answers as per the class policy.

We have documented our use of AI tools (if applicable) in a following table, as suggested in the NUS AI Tools policy. This particular document did not use any AI Tools to proofcheck and was constructed and edited purely by manual work.

1B. Exception to the Class Policy. We did not follow the CS4248 Class Policy in doing this assignment. This text explains why and how we believe we should be assessed for this assignment given the circumstances explained.

Signed, A0205572J, A0207999E, A0217512N, A0223929X, A0222101J

A Appendix

Table of syntactic features and intuitions

Feature	Intuition
Word count	A basis for regulating the following features, as longer text is more common to give higher counts
Sentence count	A basis for regulating the following features, as longer text is more common to give higher counts
First, second, third person pronoun	First and second pronouns are indicative of subjectivity
Proper nouns	Authentic new uses more proper nouns
Conjunctions	Reliable news uses less conjunctions (eg. and, but)
Superlative	Superlatives are words or phrases that indicate the highest degree of a certain quality or attribute. Reliable news uses less superlative (eg. best, worst, greatest)
Hedging words	Hedging words are words or phrases used to soften the impact of a statement. They are often used to convey uncertainty, or to avoid making a definitive statement. (eg. perhaps, probably, might)
Boosting words	Boosting words are words that are used to emphasise or amplify a statement. Used to increase the strength or intensity of the message being conveyed. (eg. absolutely, completely, definitely)
Numbers	Numbers are indicative of data being used to substantiate text
Number of consecutive all caps words	From examining data, propaganda tends to contain long consecutive capital words.