TRUTHLENS

CM3070 Computer Science Final Project

Abstract

TruthLens, based on the Fake News Detection template, is a Python based two-stage misinformation classifier. The application provides users with a lens through which they can identify misinformation along with an explanation of why it has been tagged that way.

Github link: https://github.com/nuttymakes/TruthLens

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1. Introduction

Misinformation and disinformation have been persistent features of human communication, from propaganda coins [1] in Roman times to modern efforts to influence elections and referendums [2]. Recent advancements such as large language models (LLMs), generative AI, and the widespread adoption of social media have exponentially increased the production and dissemination of misleading content. This poses both technical and cognitive challenges. For example, 75% of Americans overestimate their ability to distinguish between legitimate and fake news headlines [3]. This highlights the urgent need for tools that not only detect misinformation, but also help users critically evaluate its content through clear explanations.

The spread of misinformation has significant consequences, from undermining public trust in mainstream media [4] to triggering conflicts between individuals [5]. Addressing this issue is essential to reducing harm from false narratives and maintaining informed democracies. Diverse user groups, such as journalists, educators, social media platforms, and individual consumers, face unique challenges in navigating misinformation. Journalists must verify breaking news quickly, educators need tools to teach media literacy, social media platforms must address misinformation at scale, and individuals often lack the means to assess credibility. This project addresses these challenges by introducing categorisation and explainability into automated misinformation detection, empowering users to better evaluate the content they encounter.

To effectively combat misinformation, it is crucial to understand its diverse forms. The term “fake news” has evolved to encompass a wide range of misleading content and has become weaponised in political discourse, as noted by Vosoughi et al. [6]. This report instead uses the term “misinformation”, which avoids political connotations and better represents the spectrum of misleading content. Building on Molina et al.’s [7] taxonomy of seven misinformation types - false news, polarised content, satire, misreporting, commentary, persuasive information, and citizen journalism - this project employs a nuanced framework to detect and categorise misinformation accurately. These categories are outlined in the table below.

Misinformation Type	Characteristics	Examples
Fabricated content	Completely false content created with the intent to deceive.	Fake reports of events that never occurred; entirely false claims about public figures
Polarised content	True events or facts presented selectively to promote a biased narrative, often omitting critical context.	Partisan news articles highlighting one side of a political argument while ignoring counterpoints.
Satire	Content intended to entertain or provoke thought through humour, exaggeration, or irony. Often misunderstood.	Satirical articles from outlets like “The Onion” being shared as if they are factual news.
Misreporting	Incorrect information shared unintentionally, often due to errors or lack of verification.	A news outlet incorrectly reporting election results due to early or inaccurate data.
Commentary	Opinion-based content reflecting the writer’s interpretation or viewpoint, often lacking factual grounding.	Editorials or blogs expressing subjective opinions without substantial evidence.
Persuasive information	Content designed to persuade or influence the audience, often including marketing and propaganda.	Politically motivated propaganda campaigns, advertisements disguised as objective news articles.
Citizen journalism	User-generated content that may lack professional journalistic standards, leading to error or bias.	Social media posts about breaking news that spread unverified or incorrect details.

FIGURE 1 - MOLINA ET AL. MISINFORMATION TAXONOMY

Traditional misinformation detection methods rely on binary classification - labelling content as true or false - but this approach oversimplifies the problem. Misleading content often exists on a spectrum, requiring more granular categorisation to inform users. To foster media literacy and critical engagement, users need to be able to distinguish whether a piece of content is entirely fabricated (false news) or presented selectively to promote bias. By moving beyond binary classification, this project aims to improve detection systems and contribute to a better understanding of misinformation.

While categorisation and explainability are key components of misinformation detection, speed and scalability are equally vital in addressing its rapid spread. Real-time identification of misinformation is necessary to mitigate its rapid spread. Vosoughi et al. found that fake news stories spread farther and faster than true ones, driven by their novelty and emotionally charged framing [6]. Manual fact-checking, while often highly accurate, is time-consuming, requires domain expertise, and is unable to keep pace with the volume of content especially during high-volume events such as elections. Balancing these demands, this project employs natural language processing (NLP) and machine learning (ML) techniques to enable scalable and efficient misinformation detection.

By integrating explainability and multi-class categorisation, this project bridges a critical gap in misinformation detection. It combines technical innovation with a user-centric design to move beyond traditional methods, aligning detection strategies with the nuanced realities of misinformation while fostering critical media literacy.

(Introduction: 744 words)

2. Literature Review

The proliferation of misinformation presents significant challenges to society, making its detection a critical research area. This review evaluates current methodologies, datasets, industry tools, and the challenges associated with misinformation detection. It also highlights the gaps and insights that inform the design of this project.

2.1 Methodologies

Approaches to misinformation detection are broadly divided into manual and automated methods. Manual methods, such as expert analysis and crowdsourced verification, yield high accuracy but are resource-intensive and infeasible for large-scale applications (Tajrian et al. [8]). Automated methods, such as those this project employs, provide scalability and adaptability.

2.1.1 Traditional Machine Learning Approaches

Traditional machine learning models like Logistic Regression (LR), Random Forest (RF), and Support Vector Machines (SVM), have demonstrated strong performance in binary classification tasks. These models rely on feature engineering to extract characteristics like word frequencies and sentiment, which inform predictions.

- Adeyiga et at. demonstrated that logistic regression achieved an impressive accuracy rate of over 97% in binary classification tasks [9]. However, their study revealed that these models struggle with nuanced content requiring contextual understanding such as satire and polarised reporting.
- Sudhakar and Kaliyamurthie highlighted the interpretability of these models but emphasised their limitations in evolving misinformation scenarios due to reliance on static feature sets [10].

Critical insight: While traditional ML methods are effective for binary classification, their reliance on feature engineering makes them unsuitable for nuanced multi-class classification. Deep learning approaches are better suited for this.

2.1.2 Deep Learning Approaches

Deep learning methods, including Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Transformer-based architectures (e.g., BERT and RoBERTa), have revolutionised misinformation detection. These methods eliminate the need for manual feature engineering by learning patterns and contextual relationships directly from data.

- Li et al. found that BERT significantly outperformed traditional models, achieving an F1 score of 0.92 in fake news classification [11]. Its ability to capture long-term dependencies makes it particularly suited for nuanced tasks.

- Ali et al. demonstrated the robustness of RNNs for handling sequential data, although they noted challenges in processing long-form text efficiently [12].
- Transformer-based models, like BERT and RoBERTa, are considered the gold standard due to their attention mechanisms, which weigh input text elements based on relevance. However, their computational costs are substantial.

Critical insight: Transformer-based architectures are well-suited for fine-grained multi-class classification. While deep learning methods offer unparalleled accuracy, their opaque decision-making processes pose challenges for explainability. This project aims to incorporate Explainable AI (XAI) techniques to address this limitation, ensuring transparency in predications.

2.1.3 Binary vs Multi-Class Classification
The majority of existing work focuses on binary classification (e.g. fake vs. real). While this approach simplifies implementation and evaluation, it oversimplifies the problem, as misinformation often exists on a spectrum. Multi-class classification, which distinguishes between types of misinformation such as satire, polarised content, and hoaxes, provides richer insights. This project will utilise both binary and multi-class classification.

- Li et al. showed that BERT-based models trained on multi-class datasets like LIAR struggle with imbalanced classes, particularly underperforming on minority categories [11].
- Advanced strategies such as data augmentation and ensemble methods can mitigate these challenges, as highlighted by Adeyiga et al. [9].

2.2 Datasets
Datasets play a crucial role in automated fake news detection by providing the foundational data needed to train, validate, and benchmark detection algorithms. There are a number of prominent datasets available, most of which have a significant body of research and benchmarks. This section reviews three significant datasets—LIAR, Fake News Corpus, and ISOT—and provides a comparative analysis to highlight their applicability to different tasks in misinformation detection.

2.2.1 LIAR
LIAR is a publicly available dataset consisting of over 12,800 manually labelled short statements collected over a decade from the Politifact website [13]. Each statement in the dataset is categorized into one of six classes: True, Mostly True, Half True, Barely True, False, and Pants on Fire (a label meaning very false or completely made up). The dataset also includes rich metadata on context, subject, speaker affiliations and more.

One strength of this dataset is that it has been annotated by experts, so we know the labels are high quality. Additionally, the six classes allow for more nuanced detection than a binary approach. However, as LIAR is a politically focused dataset, its usefulness may be limited for fake news detection in other domains. Another issue to note is that it is a static dataset ending in 2017 and thus does not account for evolving misinformation tactics. The classes are also not balanced, with the “Pants on Fire” class being particularly underrepresented, which can introduce bias during model training.

2.2.2 Fake News Corpus

Fake News Corpus is a large-scale dataset containing 9.4 million articles sourced from a diverse range of websites [14]. Articles are grouped by the domains that they come from, with labels such as reliable, bias, and conspiracy. The sheer scale of the dataset is one of its major strengths. The domain-level labelling allows models to get a good understanding of the overall reliability of websites, aiding in pattern recognition across certain websites.

However, the Fake News Corpus has some noticeable limitations. Articles are not individually labelled; instead, labels are applied at the domain level and apply to any article that originated there. This can lead to inaccuracies where a website publishes a mix of true and false content. Like the LIAR dataset, the classes in this dataset are imbalanced, with reliable sources far outnumbering biased or conspiratorial ones.

2.2.3 ISOT

The ISOT Fake News Dataset [15] contains 44,898 articles, split into two balanced categories: 21,417 fake news articles and 23,481 real news articles.The real news articles are sourced from Reuters, while the fake news articles originate from websites flagged as unreliable by Politifact and Wikipedia. Unlike LIAR and Fake News Corpus, the ISOT dataset offers a balanced class distribution, reducing the risk of bias in binary classification tasks.

A major strength of the ISOT dataset is its longer text samples, which provide richer context for natural language processing models and make it particularly suitable for tasks that require deep semantic understanding. However, the narrow topical focus of the dataset is a limitation, with much of the content being political or world news. Furthermore, the dataset has binary labels, making it less suitable for advanced tasks, like explainability or multi-class classification.

2.2.4 Misinformation & Fake News text dataset

This misinformation dataset [16] contains 78,617 articles, split into two categories: 34,975 true articles from traditional media sources such as Reuters and the New York Times, and 43,642 fake articles from a variety of websites and previously published datasets.

One strength of this dataset is that it covers a wide range of sources which can help protect against overfitting. A limitation is that the dataset consists only of the index and the text, no other metadata or context is available.

2.2.5 Comparative Analysis

While each dataset has its strengths, their limitations highlight key challenges in fake news detection. The LIAR dataset excels in fine-grained classification but is domain-specific and suffers from class imbalance. The Fake News Corpus provides unparalleled scale and domain-level insights but lacks individual article labelling. The ISOT dataset, with its balanced classes and rich text samples, is ideal for binary classification but limited in its topical diversity and metadata richness.

Dataset	Size	Labels	Domain	Strengths	Weaknesses
LIAR	12,836	6 classes (True, Half True, etc.)	Politics	Expert annotations, rich metadata	Static, imbalanced classes, narrow topical focus
Fake News Corpus	9.4 million	Domain based (Reliable, Conspiracy etc.)	Diverse websites	Large scale, domain level patterns	No article-level labelling
ISOT	44,898	2 classes (Fake, Real)	Politics / World News	Balanced classes, longer text	Static, Narrow topical focus, lacks metadata
Misinformation & Fake News	78,617	2 classes (Fake, Real)	Diverse websites	Longer text, variety of sources	Lacks metadata

FIGURE 2 - DATASET COMPARISON

2.3 Industry tools

Industry tools demonstrate practical applications of misinformation detection. These tools leverage diverse methodologies, including crowd-sourced verification, algorithmic analysis, and AI-driven evaluations. This section explores three prominent tools - X/Twitter’s misinformation measures, Google Fact Check Explorer, and Facticity.ai - and evaluates their effectiveness, scalability, and accessibility.

2.3.1 X/Twitter

X, formerly known as Twitter, has faced scrutiny for the volume of misinformation on its platform [17]. A variety of tools to address misinformation, utilising both algorithmic and crowd-sources approaches, have been implemented [18]. These include user reporting mechanisms, "community notes" that allow users to add contextual explanations to posts, and curated collections of trusted information under "X Moments". Additionally, the platform can limit the visibility of, or remove, flagged content.

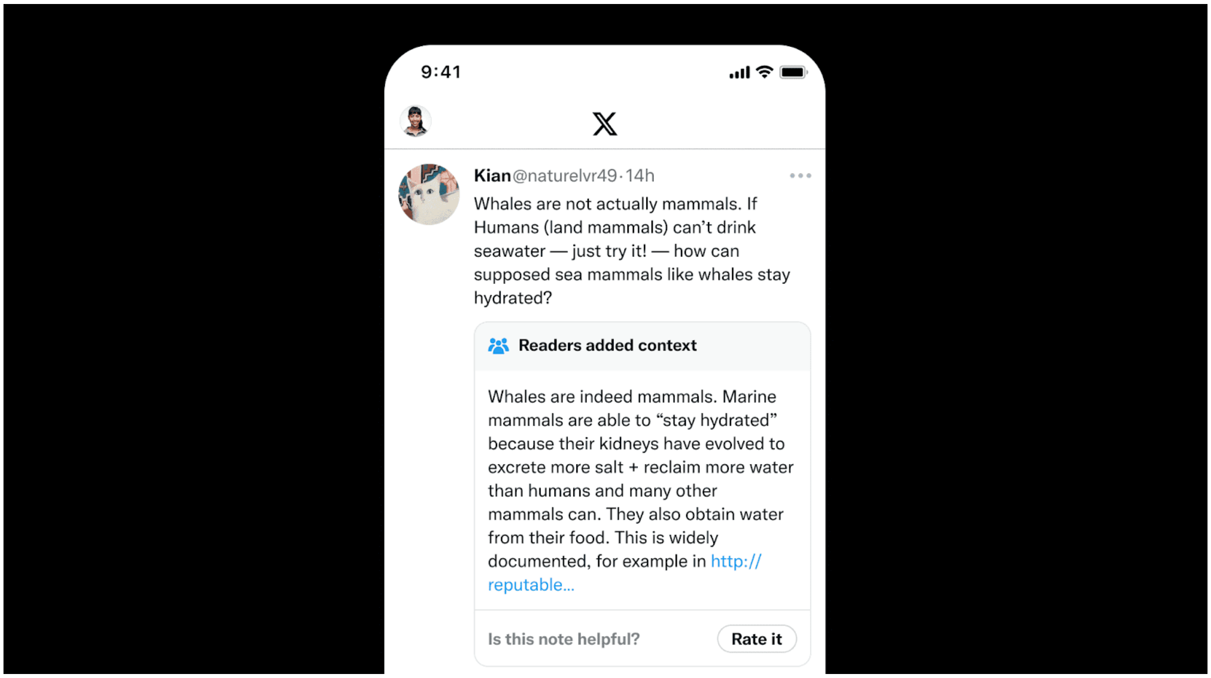

FIGURE 3 - COMMUNITY NOTE ON X

While these measures demonstrate proactive engagement, they are not without limitations. Scalability remains a challenge, as community notes or crowdsourced knowledge are not universally applied across posts. Furthermore, smaller platforms cannot replicate this approach due to their limited user bases. The reliance on voting mechanisms for community notes also raises concerns about potential gamification by malicious actors seeking to promote specific narratives.

2.3.2 Google Fact Check Explorer

Google Fact Check Explorer aggregates fact-checks from reputable organisations worldwide, enabling users to quickly verify the credibility of news stories or claims [19]. By searching for a headline or claim, users can access a range of assessments and contextual information from sources such as Politifact, Snopes, and FactCheck.org.

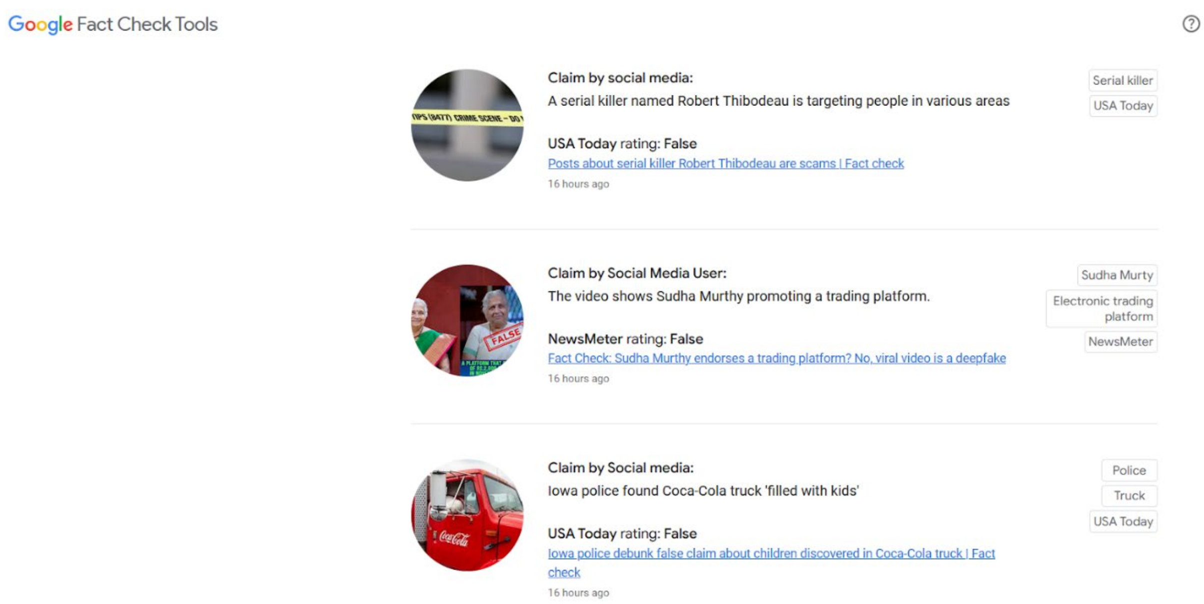

FIGURE 4 - GOOGLE FACT CHECK TOOLS

A significant advantage of Fact Check Explorer is its integration of diverse sources, offering a comprehensive overview of a claim's credibility. However, it relies heavily on manual fact-checking processes, which limit its speed and scalability, particularly during high-volume events. Additionally, the quality of results depends on the presence of fact-checks for specific claims, meaning that the tool may lack coverage for newer or less widely reported topics.

2.3.3 Facticity.ai

Facticity.ai is a commercial AI-powered tool designed to assess the credibility of online content [20]. It leverages natural language processing and machine learning algorithms to analyse articles, blogs, and other digital media. It provides users with a trustworthiness score based on linguistic patterns, source reliability, and content metadata. It also offers detailed feedback on why a specific piece of content might be misleading, making it particularly useful for educators, journalists, and researchers aiming to combat misinformation.

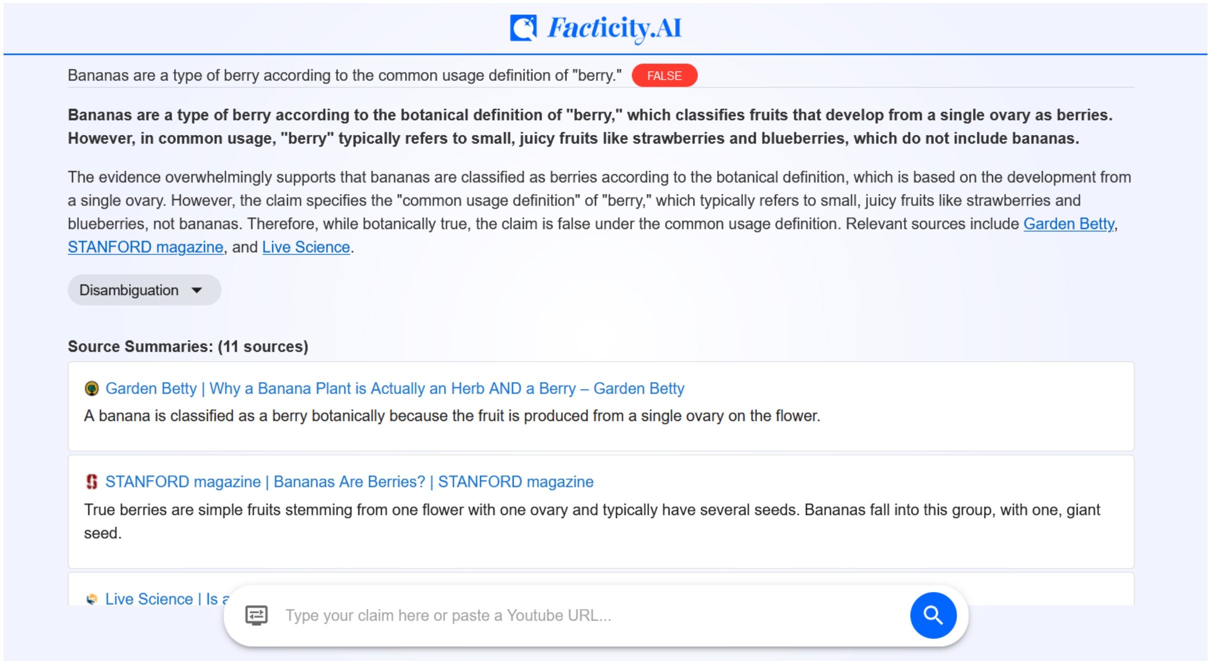

FIGURE 5 - FACTICITY.AI INTERFACE

A notable advantage of Facticity.ai is its explainability, as the tool highlights specific elements of a text that influenced its trustworthiness rating. However, one limitation is that its effectiveness depends on the robustness of its training data, which may not fully capture emerging misinformation trends or domain-specific nuances. Additionally, as a proprietary tool, it may not be accessible to all users without subscription or licensing fees.

2.4 Challenges and gaps

Despite advancements in language models, significant challenges remain in misinformation detection. This project addresses key challenges identified in the literature:

- **Class imbalance:** Many datasets are imbalanced, leading to biased predictions. This skews model training and evaluation. This project’s custom dataset will ensure balanced training data.
- **Explainability:** Many models function as “black boxes”, making it difficult to interpret why a particular piece of content was classified in a specific way. This project integrates Explainable AI (XAI) techniques to enhance user trust and understanding.
- **Evolving misinformation patterns:** Misinformation evolves rapidly in terms of form, targets, and platforms. This necessitates adaptive models capable of generalising across datasets and contexts. This project employs transfer learning to generalise across contexts.

Addressing these challenges requires strategies such as transfer learning for adaptability, data augmentation for balancing datasets, and the incorporation of explainable AI techniques to improve model transparency.

(Literature review:1,888 words)

3. Design

3.1 Project Objectives

The primary objective of this project is to build a two-stage pipeline for misinformation classification:

1. Binary classification (Stage 1): Distinguish between real news and misinformation using the ISOT dataset. This ensures robust detection at the first stage, leveraging an established dataset.
2. Multi-class classification (Stage 2): Further classify content identified as misinformation into one of five categories, based on an adaption of Molina et al.'s taxonomy. A custom dataset will support this nuanced classification.

The scope of the project is limited to text-based, English language content, explicitly excluding images, videos and audio files.

A secondary objective is to enhance the explainability of classification results, aiming to provide users with interpretable insights into why content was classified in a particular way.

The project aims for high accuracy and reliability, with measurable performance goals. Ethical considerations, including bias mitigation and responsible dataset usage, will guide the design and implementation of the pipeline.

3.2 Justification of design choices

The two-stage design is justified by the domain's requirements:

- Binary classification efficiently filters out real news.
- Multi-class classification addresses the nuanced nature of misinformation, aligning with the goal of detailed categorisation.
- Explainability addresses the user need for trust in automated systems and supports ethical AI practices.

3.3 Data Preparation

Data preparation for the project will occur in two phases to align with the two-stage pipeline:

3.3.1 Phase 1: Real vs. Fake News Classification

The first stage leverages the ISOT dataset, which contains almost 45,000 long-form articles evenly distributed between two classes: real and fake news [15]. The dataset is well-suited for binary classification due to its balance and scale. Using an existing dataset eliminates the need for custom data collection for this phase and accelerates development.

Phase 1 preprocessing includes tokenisation, lemmatisation, stop-word removal, and text normalisation. These steps ensure consistency and reduce noise in the input data, enabling efficient model training.

3.3.2 Phase 2: Misinformation Typology Classification

For the second stage, a new dataset will be created to classify misinformation into one of four categories, based on an adaption of the Molina taxonomy. Approximately 400 articles per label will be collected, resulting in a balanced dataset of 1,600 samples. Ethical considerations, such as compliance with scraping regulations and proper attribution of sources, will guide data collection efforts. Additionally, to ensure diversity and representativeness, multiple sources will be used for each category.

The dataset will be created using the following steps:

- **Data collection:** Articles will be scraped from publicly available sources, including existing datasets, news outlets, satire websites, and independent journalism platforms, chosen for their relevance to specific misinformation categories. Tools such as Python's BeautifulSoup and Scrapy libraries will facilitate efficient data scraping.
- **Preprocessing:** The collected articles will be cleaned to remove advertisements, HTML tags, and non-text content. Additionally, the standard preprocessing tasks outlined in phase 1 will be completed.
- **Annotation:** Articles will be manually reviewed with clear guidelines to ensure accurate labelling.

3.3.3 Dataset split

For both phases, the final datasets will be split into training and test sets using an 80-20 ratio.

3.4 Feature Extraction

Feature extraction is a critical step in transforming raw text into numerical representations suitable for machine learning models.

3.4.1 Phase 1: Real vs. Fake News Classification

For the first phase, feature extraction will focus on capturing key linguistic and textual characteristics that differentiate real news from misinformation. The following approaches will be employed:

- **TF-IDF** (Term Frequency- Inverse Document Frequency): Quantifies the importance of words in an article relative to the entire dataset, emphasising unique terms.
- **N-Grams:** Bigrams and trigrams capture contextual patterns like repetitive phrases.
- **Readability metrics:** Features such as word count, sentence count, and Flesch reading ease will be calculated to account for the stylistic differences between real and fake articles.

3.4.2 Phase 2: Misinformation Typology Classification

For the second phase, in addition to TD-IDF, a more nuanced feature set will be used to capture the stylistic and content-based differences across the four misinformation types:

- **Topic modelling:** Latent Dirichlet Allocation (LDA) identifies thematic patterns within articles.
- **Sentiment analysis:** Sentiment polarity and subjectivity scores distinguish categories such as polarised content and opinion
- **Named Entity Recognition (NER):** Identifies named entities such as people, places, and organisations to detect fabricated content

3.5 Model Selection

Different models will be evaluated for each phase, prioritising accuracy.

3.5.1 Phase 1: Real vs. Fake News Classification

For binary classification, the following models will be considered:

- **Logistic regression:** Serves as a baseline model due to its simplicity and interpretability. This model was noted to be very effective in the literature review.
- **Support Vector Machines** (SVM): Effective for high-dimensional text data, offering robust decision boundaries.

- **Random forest:** Ensemble-based method known for its feature importance insights.

3.5.2 Phase 2: Misinformation Typology Classification

For multi-class classification, the following models will be considered:

- **Logistic Regression:** A linear model, valued for its simplicity and ease of interpretation.
- **Multinomial Naive Bayes:** Leverages probabilistic assumptions, effective with high-dimensional sparse features.
- **XGBoost:** Provides scalability and strong performance in multi-class settings.
- **Neural networks:** A feed-forward architecture explores non-linear relationships in the feature space.

3.6 Pipeline architecture

The pipeline is divided into two stages: Binary Classification and Multiclass Classification. The stages are connected sequentially, and the architecture incorporates feature extraction, model training, and explainability at each stage.

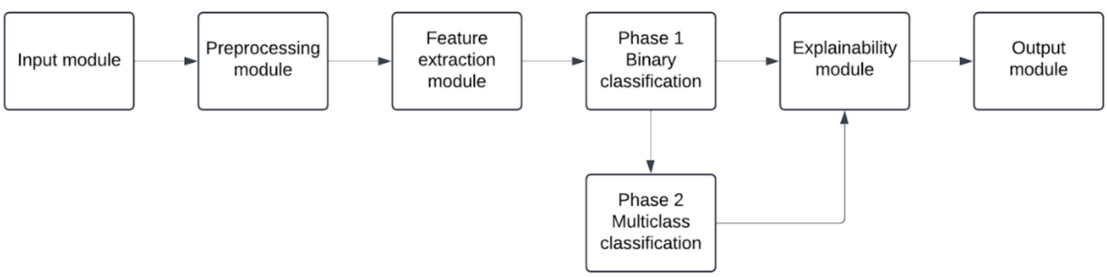

FIGURE 6 - PIPELINE ARCHITECTURE

3.6.1 Input Module

- **User Input**: Users can input a raw text article.

3.6.2 Preprocessing Module

- **Tokenisation**: Split the text into individual tokens for feature extraction.
- **Text Normalisation**: Case conversion, and removal of stop words, punctuation, and special characters.

- **Readability Metrics**: Calculate readability metrics such as Flesch reading ease, word count and sentence count.

3.6.3 Feature Extraction Module

Stage 1: Binary Classification

- **TF-IDF Vectorizer**: Quantifies word importance across the dataset.
- **Readability Metrics**: Compute features like average sentence length and lexical diversity.
- **Vector Output**: A feature vector for each article, ready for the binary classifier.

Stage 2: Multi-Class Classification

- **Topic Modelling (LDA)**: Extract thematic features aligning with misinformation categories.
- **Sentiment Analysis**: Polarity and subjectivity scores for the text.
- **Named Entity Recognition (NER)**: Detect names, places, and organizations to identify fabricated content.
- **Vector Output**: An enriched feature vector for the multi-class classifier.

3.6.4 Classification Module

Stage 1: Binary Classification

- **Model Options**:
  - Logistic Regression
  - Support Vector Machine (SVM)
  - Random Forest
- **Output**: Probability scores for "Real" or "Fake", with “Fake” proceeding to Stage 2.

Stage 2: Multi-Class Classification

- **Model Options**:
  - Linear Regression
  - Multinomial Naive Bayes
  - XGBoost
  - Feedforward Neural Network

- **Output**: A predicted label for one of four misinformation types:
  - Fabricated Content
  - Polarised Content
  - Satire
  - Commentary / Opinion

3.6.5 Explainability Module

- **SHAP (SHapley Additive exPlanations)**:
  - For binary classification, highlight key words and phrases that influenced the real/fake decision.
  - For multi-class classification, explain the reasoning behind the predicted misinformation type.
- **User-Friendly Output**:
  - Highlighted text sections in the original input with explanations.
  - Visual summaries (e.g., bar charts) showing feature contributions.

3.6.6 Evaluation and Feedback Module

- **Evaluation Metrics**:
  - For both stages: Accuracy, Precision, Recall, F1-Score, Confusion Matrix.
- **Feedback Collection**:
  - Allow users to provide feedback on predictions and explanations.
  - Feedback data can be used to improve model performance iteratively.

3.6.7 Output Module

- **Binary Classification Results**:
  - “Real” or “Fake” with a confidence score.
- **Multi-Class Classification Results**:
  - Misinformation type (if applicable) with a confidence score.
- **Explanations**:
  - Key contributing factors to the classification.

- **User Interface**:
  - UI for displaying results and explanations.
  - Options for exporting results (e.g., CSV, PDF).

3.7 Key Technologies

This project relies on Python as the primary programming language due to its extensive ecosystem of libraries for machine learning, data preprocessing, and natural language processing. The development environment will primarily use Jupyter Notebooks for iterative development and experimentation, sometimes through Google Colab which provides additional processing power.

Key technologies and tools include:

- Programming language: **Python**, chosen for its versatility and robust support for data science workflows.
- Development environment: **Jupyter Notebooks**, enabling interactive development and seamless integration of code, visualisations, and documentation.
- Data Collection:
  - **BeautifulSoup**: For HTML parsing and web scraping
- Text Preprocessing:
  - **NLTK** (Natural Language Toolkit): Tokenisation, stop-word removal, and lemmatisation.
  - **SpaCy**: Named Entity recognition (NER) and dependency parsing.
  - **TextBlob**: Sentiment analysis and text normalisation
- Feature extraction:
  - **TF-IDF:** via scikit-learn's TfidfVectorizer.
  - **N-grams**: extracted using CountVectorizer in scikit-learn.
  - **Topic modeling**: Gensim for Latent Dirichlet Allocation (LDA).
- Classification models:
  - **Scikit-learn:** Logistic regression, Support Vector Machines (SVM), Random Forest, and Multinomial Naive Bayes.

  - **XGBoost**: A high-performance library for gradient-boosted trees, used for multiclass classification
  - **Tensorflow**: for building and fine-tuning neural network models.
- Explainability tools:
  - **SHAP** (SHapley Additive exPlanations): for feature importance analysis and user facing explanations
- User interface:
  - **Flask**: to create a lightweight backend for accepting user inputs such as text articles or URLs
  - **Newspaper3k**: to scrape and extract article text from URLs provided by users
  - **Streamlit**: For building an interactive web-based interface to display classification results and explanations.

3.8 Evaluation and Testing

For both phases, model performance will be evaluated using:

- **Accuracy:** The primary metric for assessing classification success
- **Precision, Recall, and F1-Score:** To ensure balanced performance, particularly for classes that may be harder to distinguish. This is particularly important for Phase 2.
- **Confusion matrix analysis:** To identify areas of misclassification.
- **Explainability validation:** Tools like SHAP (SHapley Additive exPlanations) analyse feature importance and provide user-facing interpretability.

Success metrics for this project include:

- Achieving classification accuracy of at least 90% in Stage 1
- An F1 score of at least 0.60 across all classes in Stage 2
- High-quality explainability for classification results, validated through a user-focused evaluation process.

Additionally, stress testing will be performed by testing the system on edge cases such as short form content, and mixed-genre content. Should time allow, some scalability testing will be performed to evaluate pipeline efficiency with large-scale inputs to simulate real-world deployment.

3.9 Plan of Work

The proposed timeline for this project runs from January 1st 2025 to submission on March 31st 2025. The project plan is visualised in the Gantt chart below, and includes seven workstreams, some of which can happen concurrently.

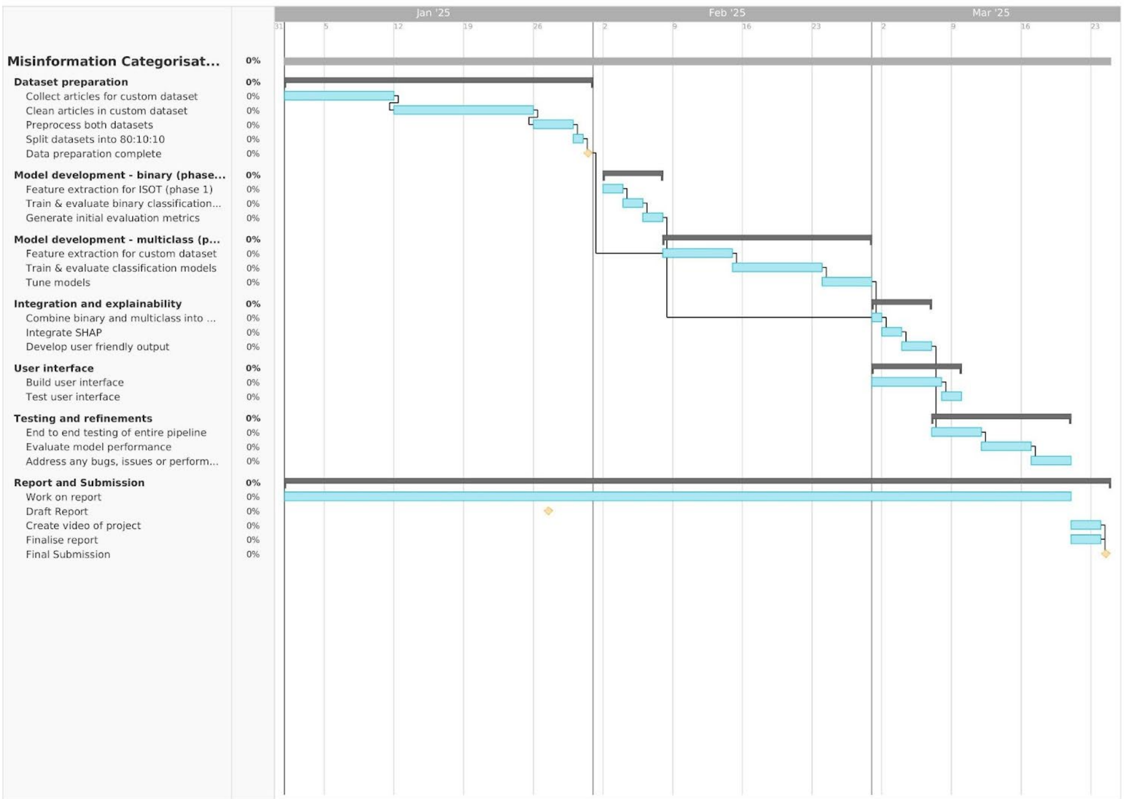

FIGURE 7 - GANTT CHART FOR PROJECT

A simplified overview of this plan is as follows:

- Dataset preparation (January 1 - 31): Much of the time in this stage will be spent collecting and cleaning the data for the custom dataset. By the end of this phase, both datasets will be ready.
- Binary model development (February 2 - 7): Implement binary classification, phase 1 of the two-stage pipeline. Model selection, tuning and evaluation should happen here.

- Multiclass model development (February 8 - 28): Implement multiclass classification, phase 2 of the two-stage pipeline. Model selection, tuning and evaluation should happen here.
- Integration and explainability (March 1 - 7): Implement and test explainability features
- User interface (March 1 - 9): Build and test the user interface.
- Testing (March 7 - 20): Test the entire build, edge cases and scalability. Evaluate the models and address any bugs or performance issues.
- Report (January 1 - March 24): Iteratively work on the project report as the project advances, in preparation for the submission on March 24th.

(Design:1,899 words)

4. Implementation

4.1 Custom Dataset Creation

The custom dataset is the backbone of phase two of the project, and an area where significant amount of time was spent. Each article was manually selected and labelled to ensure accuracy to the class taxonomy.

4.1.1 Molina Adaption

As per the design, a custom dataset heavily based on the Molina taxonomy was created. During prototyping it was noted that while the taxonomy is a useful tool in evaluating the type of an existing piece of misinformation, there is a lot of overlap between the labels. A brief overview of the adaptions to the taxonomy are noted below:

- Rather than the seven classes in the original taxonomy, this adaption has four classes.
- The misreporting class has been dropped completely. This class was used for incorrect information shared unintentionally – for example due to human error, premature reporting, or lack of verification. These types of mistakes are usually corrected or clarified once the issue has been noted. Many major publications offer “Corrections” or “Retractions” sections, so finding sources was not an issue. However, pieces without corrections are indistinguishable from “real” news, and in most cases reviewed the correction was small (e.g. incorrect home town, but correct county and country, incorrect middle name).
- The persuasive information category has been dropped. Finding sources for this category was problematic. Persuasive information in the politics realm is broadly covered by the polarised content class. State-influenced media has a similar problem. This is also a difficultly defining the line between biased content and propaganda.
- The citizen journalism category has been dropped. In reality it is very difficult to find this kind of content as many of the platforms that exist to host it require users to adhere to journalistic standards (e.g. https://bylinesnetwork.co.uk/volunteer/) or no longer exist (e.g. https://ireport.cnn.com), and on other platforms such as Reddit and Twitter/X it is very difficult to differentiate between citizen journalism and commentary.
- The fabricated content class was expanded to include AI generated content. The Molina taxonomy was created in 2019, before the proliferation of AI content that we see today. Given that Thompson, Dhaliwal et al. found that 57% of all web-based text has been AI generated or translated through an AI algorithm in their 2024 report [21], including it seemed important.

The final classes can be seen in the table below.

Misinformation Type	Characteristics	Example
Fabricated content	Completely false content, generated by a person or AI, created with the intent to deceive.	Fake reports of events that never occurred; entirely false claims about public figures.
Polarised content	True events or facts presented selectively to promote a biased narrative, often omitting critical context.	Partisan news articles highlighting one side of a political argument while ignoring counterpoints.
Satire	Content intended to entertain or provoke thought through humour, exaggeration, or irony. Often misunderstood.	Satirical articles from outlets like "The Onion" being shared as if they are factual news.
Commentary	Opinion-based content reflecting the writer's interpretation or viewpoint, often lacking factual grounding.	Editorials or blogs expressing subjective opinions without substantial evidence.

FIGURE 8 - FINAL MISINFORMATION TAXONOMY FOR PHASE 2

4.1.2 Collecting the custom dataset

The code used to scrape articles from various sources for each category can be found in the "TruthLens Data Collection" notebook.

For each source, a list of URLs was defined in a .txt file. Manually selecting and reviewing each article reduces the risk of mislabelling an article.

```
https://www.breitbart.com/middle-east/2025/01/20/icc-prosecutor-leading-charge-against-israel-meets-syrias-jihadi-overlords/
https://www.breitbart.com/politics/2025/01/20/exclusive-senate-sources-fbi-senate-democrats-reason-tulsi-gabbards-slow-walked-confirmation/
https://www.breitbart.com/politics/2025/01/20/trump-in-inauguration-speech-official-policy-of-u-s-government-is-there-are-only-two-genders-male-and-female/
https://www.breitbart.com/latin-america/2025/01/20/javier-milei-condemns-brazil-for-keeping-bolsonaro-from-trump-inauguration/
https://www.breitbart.com/politics/2025/01/20/president-donald-trump-declares-national-emergency-southern-border/
https://www.breitbart.com/politics/2025/01/20/trump-promises-release-jfk-rfk-mlk-assassination-records-coming-days/
https://www.breitbart.com/politics/2025/01/20/donald-trump-lights-up-political-class-election-a-mandate-to-reverse-horrible-betrayal-of-americans/
https://www.breitbart.com/sports/2025/01/20/espn-to-air-national-anthem-and-mlk-themed-content-before-national-championship-game/
https://www.breitbart.com/2024-election/2025/01/20/exclusive-peter-schweizer-slams-biden-family-pardons-we-have-never-had-such-a-self-serving-and-corrupt-president/
https://www.breitbart.com/politics/2025/01/20/president-donald-trump-saved-god-make-america-great-again/
```

FIGURE 9 - EXAMPLE OF URLS FROM BREITBART.TXT

For each source a custom scraping function was defined. This was necessary as there is so much variance between the structures of different websites. Here's an example of a scraping function used for The Onion website:

```python
    article_data = {
        "title": "",
        "text": "",
        "site": "",
        "date": "",
        "category": "",
        "class": "Satire",
        "url": url
    }

    response = requests.get(url)
    if response.status_code == 200:
        soup = BeautifulSoup(response.content, 'html.parser')

        #title
        title_meta = soup.find('meta', property='og:title')
        article_data["title"] = title_meta['content'] if title_meta else "Title not found"

        #URL
        url_meta = soup.find('meta', property='og:url')
        article_data["url"] = url_meta['content'] if url_meta else url

        #site name
        site_name_meta = soup.find('meta', property='og:site_name')
        article_data["site"] = site_name_meta['content'] if site_name_meta else "Site name not found"

        #published date
        published_date_meta = soup.find('meta', property='article:published_time')
        article_data["date"] = published_date_meta['content'] if published_date_meta else "Published date not found"

        #category
        category_element = soup.find('div', class_='taxonomy-category')
        category_link = category_element.find('a') if category_element else None
        article_data["category"] = category_link.text.strip() if category_link else "Category not found"

        #article copy
        content_div = soup.find(
            "div",
            {"class": lambda x: x and "entry-content" in x and "single-post-content" in x}
        )
        if content_div:
            paragraphs = content_div.find_all("p")
            full_text = " ".join(p.get_text(strip=True) for p in paragraphs)
            article_data["text"] = clean_text(full_text)
        else:
            article_data["text"] = "Article text not found"
    else:
        print(f"Failed to fetch the webpage: {url}. Status code: {response.status_code}")

    return article_data
```

FIGURE 10 - EXCERPT FROM SCRAPE_ONION_ARTICLE FUNCTION

Finally, all the different articles were combined into one master file.

```
Columns: [title, text, site, date, category, class, url]
Index: []
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1600 entries, 0 to 1599
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype 
---  ------    --------------  ----- 
 0   title     1250 non-null   object
 1   text      1600 non-null   object
 2   site      1600 non-null   object
 3   date      1600 non-null   object
 4   category  1500 non-null   object
 5   class     1600 non-null   object
 6   url       1600 non-null   object
dtypes: object(7)
memory usage: 87.6+ KB
```

FIGURE 11 - MASTER_DF.INFO()

4.1.3 The Final Dataset

The final dataset consists of 1,600 manually reviewed and labelled articles from a variety of sources, as outlined in the table below. Detailed labelling notes can be found in the appendix, as can detailed notes about the sources and examples of an article from each source.

Class	Sources	Notes
Fabricated Content	LIAR dataset (350) ChatGPT (25) DeepSeek (25)	Only content from the "pants-fire" category in the LIAR dataset was used.
Polarised Content	The Conservative Woman (100) The Canary (100) Breitbart (100) Daily Kos (100)	Even split between left and right leaning articles. Both US and UK sources were included.
Satire	The Onion (100) Babylon Bee (100) The Daily Squib (100) Waterford Whispers (100)	Sources from the US, UK and Ireland.
Commentary	The Guardian (50) Washington Examiner (100) European Conservative (100) Rolling Stone (100) Nature (50)	A mixture of left leaning, right leaning and neutral sources.

FIGURE 12 - CUSTOM DATASET CLASS OVERVIEW

4.2 Data Preprocessing and Exploration

4.2.1 Data Preprocessing Phase 1 and Phase 2

In the prototype, some basic binary classifications were tested on a sample from the ISOT dataset. This led to some suspiciously high accuracy ratings such as 0.995 out of the box with no tweaking or tuning.

Random Forest

In [13]:

```
rf_model = RandomForestClassifier()
rf_model.fit(X_train, y_train)
rf_pred = rf_model.predict(X_test)
print("Random Forest Accuracy:", accuracy_score(y_test, rf_pred))
print("Random Forest Classification Report:\n", classification_report(y_test, rf_pred))
```

```
Random Forest Accuracy: 0.995
Random Forest Classification Report:
               precision    recall  f1-score   support

           0       0.99      1.00      1.00       103
           1       1.00      0.99      0.99        97

    accuracy                           0.99       200
   macro avg       1.00      0.99      0.99       200
weighted avg       1.00      0.99      0.99       200
```

FIGURE 13 - RANDOM FOREST PROTOTYPE CLASSIFICATION REPORT

Further investigation revealed that there was a serious bias issue in the data – all the True articles were from Reuters, so the model was simply learning to look for that. For this reason, the decision was made to use the Misinformation Dataset [16] instead for phase 1 modelling.

For both phase 1 and phase 2 data, the same series of functions were applied. A custom function was written to find uncensor words such as “f**k” in the database. The Textacy library is then utilised to perform some preprocessing steps for example normalising whitespace or replacing URLs and brackets in the text.

```
In [9]:
basic_clean =  preprocessing.make_pipeline(
    #normalise unicode
    preprocessing.normalize.unicode,
    #fix hyphenated words
    preprocessing.normalize.hyphenated_words,
    #handle differemt types of quotation marks
    preprocessing.normalize.quotation_marks,
    #normalise whitespace
    preprocessing.normalize.whitespace,
    #remove any HTML tags that may have snuck in
    preprocessing.remove.html_tags,
    #get rid of URLs
    preprocessing.replace.urls,
    #get rid of Twitter handles
    preprocessing.replace.user_handles,
    #replace currency symbols with '__CUR__'
    preprocessing.replace.currency_symbols,
    #get rid of brackets
    preprocessing.remove.brackets
)
```

FIGURE 14 - TEXTACY PREPROCESSING

A label encoder was used to transform the labels on both datasets into numeric representations.

Phase	**Class**	**Label**
1	True	0
	False	1
2	Commentary	0
	Polarised	1
	Satire	2
	Fabricated	3

FIGURE 15 - CLASS DICTIONARY AFTER LABEL ENCODING

Next, readability metrics were calculated on the data using the textstat library. Plotting the Flesch reading ease by label lets us see at a glance that there’s a difference between the classes – “true” news (class 0) has a slightly lower Flesch score than “fake” (class 1) news, indicating that fake news is easier to read.

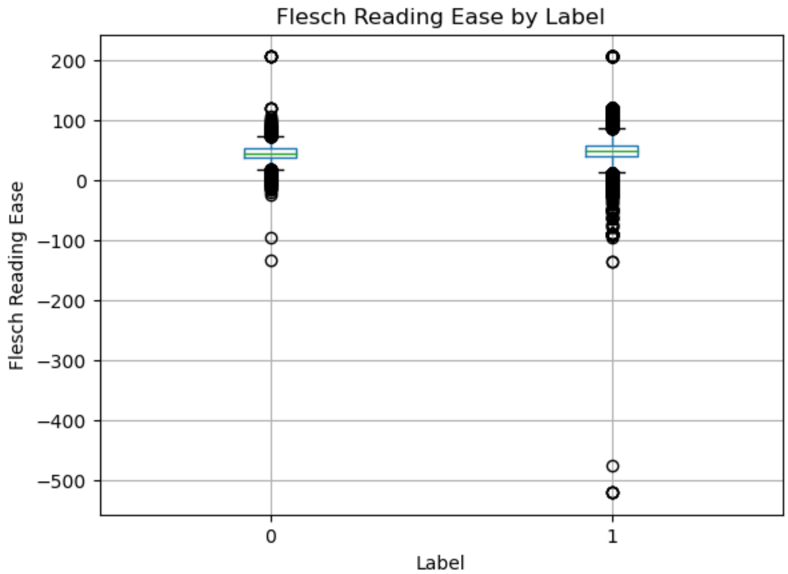

FIGURE 16 - FLESCH READING EASE BY LABEL ON PHASE 1 DATA

Next, I tested what text representation performed best – A Porter stemmer, a Snowball stemmer, WordNet lemmatizer, or a Wordnet lemmatiser with part-of-speech (POS) tagging. While the lemmatiser took longer, the results were much better than the stemmers tested. For example, both stemmers changed "president" to "presid" and "Hillary" to "hillari".

In [12]:

```
# Apply the processing functions and measure the time for each
# Porter Stemmer
start_time = time.time()
df_sample['porter'] = df_sample['content'].apply(process_porter)
print("Porter Stemmer time: {:.4f} seconds".format(time.time() - start_time))

# Snowball Stemmer
start_time = time.time()
df_sample['snowball'] = df_sample['content'].apply(process_snowball)
print("Snowball Stemmer time: {:.4f} seconds".format(time.time() - start_time))

# WordNet Lemmatizer
start_time = time.time()
df_sample['wordnet'] = df_sample['content'].apply(process_wordnet)
print("WordNet Lemmatizer time: {:.4f} seconds".format(time.time() - start_time))

# WordNet Lemmatizer with POS tagging
start_time = time.time()
df_sample['wordnetPOS'] = df_sample['content'].apply(lemmatize_passage)
print("WordNet Lemmatizer with POS tagging time: {:.4f} seconds".format(time.time() - start_time))

# Display the resulting dataframe with the new columns
df_sample.head()
```

```
Porter Stemmer time: 0.4592 seconds
Snowball Stemmer time: 0.2011 seconds
WordNet Lemmatizer time: 11.7453 seconds
WordNet Lemmatizer with POS tagging time: 0.9735 seconds
```

FIGURE 17 - STEMMING AND LEMMATISING MY DATA

A variation of the data with the stop words and punctuation removed was also created. The final outcome of this section is a dataframe for both datasets with an additional 5 columns – word_count, sentence_count, flesch_reading_ease, content_lemma and content_lemma_nostop.

Out[26]:

	content	label	word_count	sentence_count	flesch_reading_ease	content_lemma	content_lemma_nostop
0	Perdue Announces Initiative To Even The Playing Field By Giving Chickens Guns SALISBURY, MD--Emphasizing that it was an integral part of the company's mission to raise humanely sourced meat, poultry processing giant Perdue Farms announced a new initiative Tuesday to even the playing field by giving guns to chickens. "At Perdue, we always strive to ensure animals are treated with dignity and respect, and today we expand upon that commitment by handing each bird a loaded pistol and allowing them a fair chance to escape," said Perdue spokesperson Jamie Walton, describing a new policy under which each chicken would be issued a weapon with a single round in the chamber and given an opportunity to kill their captor with a well-placed bullet before they could be taken to slaughter. "They should get one clean shot. That's just good sportsmanship. So from now on, every chicken in our Perdue facilities will have free and easy access to firearms. We may lose some staff	2	207	8	45.19	Perdue Announces Initiative To Even The Playing Field By Giving Chickens Guns SALISBURY , MD -- Emphasizing that it be an integral part of the company 's mission to raise humanely sourced meat , poultry processing giant Perdue Farms announce a new initiative Tuesday to even the playing field by give gun to chicken . `` At Perdue , we always strive to ensure animal be treat with dignity and respect , and today we expand upon that commitment by hand each bird a loaded pistol and allow them a fair chance to escape , '' say Perdue spokesperson Jamie Walton , describe a new policy under which each chicken would be issue a weapon with a single round in the chamber and give an opportunity to kill their captor with a well-placed bullet before they could be take to slaughter . `` They should get one clean shot . That 's just good sportsmanship . So from now on , every chicken in our Perdue facility will have free and easy access to firearm . We may lose some staff	perdue announces initiative even playing field giving chickens guns salisbury md emphasizing integral part company mission raise humanely sourced meat poultry processing giant perdue farms announce new initiative tuesday even playing field give gun chicken perdue always strive ensure animal treat dignity respect today expand upon commitment hand bird loaded pistol allow fair chance escape say perdue spokesperson jamie walton describe new policy chicken would issue weapon single round chamber give opportunity kill captor wellplaced bullet could take slaughter get one clean shot good sportsmanship every chicken perdue facility free easy access firearm may lose staff gunshot wound everyone involve human fowl opportunity defend right press time source confirm shift balance power several

FIGURE 18 - EXAMPLE ROW FROM FINAL CLEANED OUTPUT OF PHASE 2 DATA

4.2.2 Data exploration

Some initial data exploration was done at this stage to better understand the data. Although I printed out the top n-grams for each class, and generated word clouds, it's still not very easy the difference between classes immediately as there is a lot of overlap.

```
Top bi-grams for class 1:
[('donald trump', np.int64(22026)), ('hillary clinton', np.int64(15748)), ('united states', np.int64(11773)), ('white house',
np.int64(9124)), ('new york', np.int64(6728)), ('image via', np.int64(6395)), ('president obama', np.int64(4890)), ('presiden
t trump', np.int64(4009)), ('fox news', np.int64(3839)), ('barack obama', np.int64(3405))]
Top bi-grams for class 0:
[('united states', np.int64(20250)), ('mr trump', np.int64(17293)), ('donald trump', np.int64(16035)), ('white house', np.int
64(12787)), ('new york', np.int64(10590)), ('president donald', np.int64(6791)), ('last year', np.int64(6239)), ('hillary cli
nton', np.int64(5745)), ('north korea', np.int64(5723)), ('trump say', np.int64(5651))]
```

FIGURE 19 - BINARY DATA N-GRAM EXPLORATION

4.3 Phase 1: Binary classification

For feature extraction, as outlined in the design, I wanted to extract two sets of features – TF-IDF (a statistical method used to evaluate the importance of a word in a document) and readability metrics such as Flesch reading ease. As the readability metrics were already calculated in the cleaning stage, we just need to scale them, convert them to a sparse matrix and combine horizontally with the TF-IDF features.

```
In [ ]:
#TF-IDF feature extraction with n-grams
start_time = time.time()
#replace NaN values with an empty string to resolve NaN ValueError
df['content_lemma_nostop'] = df['content_lemma_nostop'].fillna('')
vectorizer = TfidfVectorizer(max_features=5000, ngram_range=(1, 3))
X_tfidf = vectorizer.fit_transform(df['content_lemma_nostop'])
#get pre-calculated readability features
readability_features = df[['word_count', 'sentence_count', 'flesch_reading_ease']].values
#standardise readability features
scaler = StandardScaler()
readability_scaled = scaler.fit_transform(readability_features)
#convert to a sparse matrix
readability_sparse = csr_matrix(readability_scaled)
#combine TF-IDF features with the readability metrics
X_combined = hstack([X_tfidf, readability_sparse])

y = df['label']
print("Feature extraction: {:.4f} seconds".format(time.time() - start_time))

Feature extraction: 256.7663 seconds
```

FIGURE 20 - PHASE 1 FEATURE EXTRACTION

Three models from sklearn were tested on the data – Logistic Regression, Random Forest and Support Vector Machine. All three performed well, with respective accuracy scores of 0.94, 0.95 and 0.95. The decision was made to choose the LR model because while it was slightly less accurate than the others, fitting the model took only 6 seconds compared to 347 seconds for Random Forest and 4253 seconds for SVM.

Further testing was then done to see which representation of the text generated the best predictions – the raw text, the lemmatised text or the lemmatised text with stopwords removed. “Content_lemma” was the most accurate at 0.9481 so that representation was chosen.

In [ ]:
```python
def evaluate_text_representation(text_column, df):
    print("Evaluating model on ",text_column)
    start_time = time.time()
    #replace NaN values with an empty string to resolve NaN ValueError
    df[text_column] = df[text_column].fillna('')

    #get TF-IDF features for the chosen text column
    vectorizer = TfidfVectorizer(max_features=5000, ngram_range=(1, 3))
    X_tfidf = vectorizer.fit_transform(df[text_column])

    #get pre-calculated readability features
    readability_features = df[['word_count', 'sentence_count', 'flesch_reading_ease']].values
    scaler = StandardScaler()
    #standardise readability features
    readability_scaled = scaler.fit_transform(readability_features)
    #convert to a sparse matrix
    readability_sparse = csr_matrix(readability_scaled)

    #combine TF-IDF features with the readability metrics
    X_combined = hstack([X_tfidf, readability_sparse])

    y = df['label']

    #split the data into training and testing sets using the dataframe index
    train_indices, test_indices = train_test_split(df.index, test_size=0.2, random_state=999)
    X_train = X_combined[train_indices]
    X_test = X_combined[test_indices]
    y_train = y.iloc[train_indices]
    y_test = y.iloc[test_indices]

    #train a simple Logistic Regression model
    model = LogisticRegression(max_iter=1000)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    elapsed_time = time.time() - start_time

    # Evaluate and print the results
    accuracy = accuracy_score(y_test, y_pred)
    report = classification_report(y_test, y_pred)

    print(f"Results for '{text_column}':")
    print("Time elapsed: {:.4f} seconds".format(elapsed_time))
    print("Accuracy:", accuracy)
    print("Classification Report:\n", report)
    print("-" * 50)

    return accuracy, model, vectorizer
```

FIGURE 21 - FUNCTION TO EVALUATE THE PERFORMANCE OF THE MODEL ON VARIOUS TEXT REPRESENTATIONS

Next, GridSearchCV was used to tune some of the model hyperparameters. This grid search was very expensive computationally, taking almost 4 and a half hours. The parameters chosen by the GridSearch were: {'C':10, 'penalty':'l1', 'solver':'liblinear'}, with a cross validation score of 0.954.

In [6]:
```python
start_time = time.time()
#we're going to test for the best combo of regularisation type (l1 or l2), C values, and solvers
param_grid = [
    {
        #l1 regularisation
        'penalty': ['l1'],
        'C': [0.1, 1, 10],
        'solver': ['liblinear', 'saga']
    },
    {
        #l2 regularization
        'penalty': ['l2'],
        'C': [0.1, 1, 10],
        'solver': ['saga', 'sag']
    }
]

#set up the grid search
grid = GridSearchCV(LogisticRegression(max_iter=2000), param_grid, cv=3, n_jobs = -1)
grid.fit(X_train, y_train)

#print the best parameters and best score, and the time it took
print("Best parameters:", grid.best_params_)
print("Best cross-validation score:", grid.best_score_)
print("Grid Search: {:.4f} seconds".format(time.time() - start_time))
```

```
Best parameters: {'C': 10, 'penalty': 'l1', 'solver': 'liblinear'}
Best cross-validation score: 0.954254805167687
Grid Search: 15976.0700 seconds
```

FIGURE 22 - GRIDSEARCHCV IN PHASE 1

Finally, I tested this tuned model on two variations of the data – one with both TF-IDF and readability features, as described above, and the other with just the TF-IDF features. The latter performed best, with an accuracy score of 0.953. This was then saved as our final model.

In summary, the final outcome of this section is a Logistic Regression model with parameters {'C': 10, 'penalty': 'l1', 'solver': 'liblinear'}, and an accuracy score of 0.953.

4.4 Phase 2: Multi-class classification

The implementation in this phase looks very similar to the implementation in the previous phase. I begin by loading my data and splitting the content from the labels. I'll be using the content_lemma column as this performed best in phase 1. The dataset is split into training and testing sets using a stratified train-test split which helps maintain class balance.

Four different models are tested on the data first to generate a baseline – Logistic Regression, Multinomial Naïve Bayes, XGBoost and a feed-forward neural network. Much of the implementation here is relying on the sklearn library.

In [19]:
```python
start_time = time.time()
#pipeline - creates TF-IDF features then creates the logistic regression model
baseline_pipeline = Pipeline([
    ("tfidf", TfidfVectorizer(max_features=5000)),
    ("clf", LogisticRegression(max_iter=1000, random_state=999))
])

#stratified k-fold cross-validation - this ensures each fold has a similar class distribution
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=999)

#generate predictions
predicted_labels = cross_val_predict(baseline_pipeline, X_train, y_train, cv=skf, method="predict")

#calculate f1 score
f1_macro = f1_score(y_train, predicted_labels, average="macro")
print("Logistic Regression Macro F1 Score:", f1_macro)

#get classification report
report = classification_report(y_train, predicted_labels)
print("\nClassification Report for Logistic Regression:\n", report)

print("Run time: {:.4f} seconds".format(time.time() - start_time))
```

```
Logistic Regression Macro F1 Score: 0.8677662531487172

Classification Report for Logistic Regression:
               precision    recall  f1-score   support

           0       0.75      0.89      0.81       320
           1       0.85      0.73      0.78       320
           2       0.94      0.87      0.90       320
           3       0.96      0.99      0.98       320

    accuracy                           0.87      1280
   macro avg       0.87      0.87      0.87      1280
weighted avg       0.87      0.87      0.87      1280

Run time: 6.9260 seconds
```

FIGURE 23 - PHASE 2 LOGISTIC REGRESSION CODE

Next, I want to evaluate which features can help my model be more efficient. I have three custom transformers which generate different types of features – sentiment, topic modelling and named entity recognition.

```
In [24]:
#named entity recognition
class NERTransformer(BaseEstimator, TransformerMixin):
    def fit(self, X, y=None):
        return self
    def transform(self, X, y=None):
        features = []
        for text in X:
            doc = nlp(text)
            counts = {}
            for ent in doc.ents:
                counts[ent.label_] = counts.get(ent.label_, 0) + 1
            #we want to return the count of the different entities
            features.append(counts)
        return features
```

FIGURE 24 - NERTRANSFORMER CODE

I then test every combination of features to see which has the best overall performance. This is a resource intensive piece of code, running for 7958 seconds, or over 2 hours. Eventually though we can see that XGBoost with TF-IDF, named entity recognition and topic model is the best feature set, with a macro F1 of 0.8714.

```
start_time = time.time()

results = {}

for model_name, clf in models.items():
    results[model_name] = {}
    print(f"\nEvaluating model: {model_name}")
    #iterate over all combos of additional features (including TF-IDF only)
    for extra in powerset(additional_features):
        #start with TF-IDF
        components = [tfidf_transformer]
        for feat in extra:
            components.append(feature_components[feat])
        #join the features horizontally
        union = FeatureUnion(components)
        #define pipeline
        pipeline = Pipeline([
            ("features", union),
            ("clf", clf)
        ])
        #evaluate
        predicted = cross_val_predict(pipeline, X_train, y_train, cv=skf, method="predict")
        f1_macro = f1_score(y_train, predicted, average="macro")

        #create a key for this combo
        key = "tfidf"
        if extra:
            key += "+" + "+".join(extra)
        else:
            key += "_only"

        results[model_name][key] = f1_macro
        print(f"Features: {key:30s} | Macro F1: {f1_macro:.4f}")


print("Run time: {:.4f} seconds".format(time.time() - start_time))
```

FIGURE 25 - FUNCTION TO TEST VARIOUS COMBOS OF FEATURES

Once the correct feature set has been chosen, I again use a GridSearch to find the best hyperparameters.

Grid Search

In [18]:
```
start_time = time.time()
param_grid = {
    "clf__max_depth": [3, 5, 7],
    "clf__learning_rate": [0.01, 0.1],
    "clf__subsample": [0.8, 1.0]
}
skf = StratifiedKFold(n_splits=3, shuffle=True, random_state=999)
grid_search = GridSearchCV(estimator=final_pipeline, param_grid=param_grid, scoring="f1_macro", cv=skf, n_jobs=1, verbose=1

grid_search.fit(X_train, y_train)
print("Best Parameters:", grid_search.best_params_)
print("Best Macro F1 Score (CV):", grid_search.best_score_)

best_model = grid_search.best_estimator_
y_pred_test = best_model.predict(X_test)
print("\nTest Set Classification Report:")
print(classification_report(y_test, y_pred_test))
print("Test Set Macro F1 Score:", f1_score(y_test, y_pred_test, average="macro"))

print("Run time: {:.4f} seconds".format(time.time() - start_time))
```

FIGURE 26 - GRID SEARCH FOR XGBOOST

4.5 Explainability and User Interface

Unfortunately due to time constraints, I did not succeed in creating any explainability content, or user interface.

(Implementation:1,553 words)

5. Evaluation

5.1 Custom Dataset Creation

Creating the custom dataset was a crucial part of this project. Despite allocating a significant amount of time to this work, collecting and cleaning the data took much longer than expected. Aside from the technical work of creating individual scraping functions for 13 separate websites, the time required to read and evaluate each website was substantial but necessary. However, these delays cascaded delays down the project, resulting in a reduced scope and outcome.

I am very happy with the resulting dataset and think that this part of the project was very successful. The strict labelling guidelines, as well as using multiple sources for each class meant longer development times, but resulted in a robust, balanced dataset. While this detail-oriented approach resulted in a great dataset, it does mean that this part of the project is not scalable which is a limitation.

One other limitation to note is the dataset size – at 1,600 lines it is relatively small for a dataset, particularly when it comes to deep learning models.

Possible extensions to this part of the project would be to increase the size of the dataset by adding more sources to the existing classes, or by implementing other classes from the Molina et al. taxonomy for example citizen journalism.

5.2 Phase 1: Binary classification

The aim of this phase was to develop a binary classifier that could tell misinformation from real information, with an accuracy of at least 90%. The final model had an accuracy of 0.95, so this stage was a success. Tuning moved the model from 0.942 to 0.954, as can be seen in the series of tables below. The model chosen at each stage is highlighted with green.

Initial tests	Logistic Regression	Random Forest	Support Vector Machine
Accuracy	0.942	0.952	0.95
Time taken (seconds)	6	347	8787

FIGURE 27 - PHASE 1 INITIAL MODEL TESTING

Text representation	'content'	'content_lemma'	'content_lemma_nostop'
Accuracy	0.940	0.948	0.942

FIGURE 28 - PHASE 1 TEXT REPRESENTATION TESTING

Features	TF-IDF+Readability	TF-IDF
Accuracy	0.947	0.954

While an accuracy of 0.954 seems very good, we can still investigate some of the misclassified rows to see if we can ascertain any trends. First, we draw out the confusion matrix:

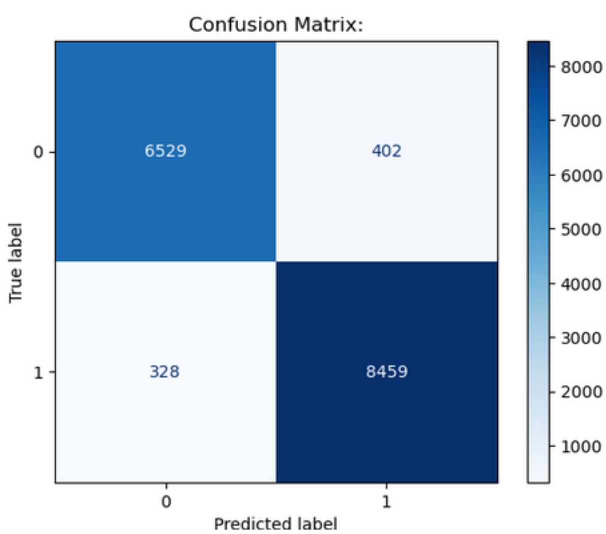

FIGURE 29 - PHASE 1 FINAL MODEL CONFUSION MATRIX

There are slightly more false positives (402) than false negatives (328), but both classes show robust performance with high precision and recall for both classes. This is also reflected in the Receiver operating characteristic (ROC) curve which has an area under curve of 0.99.

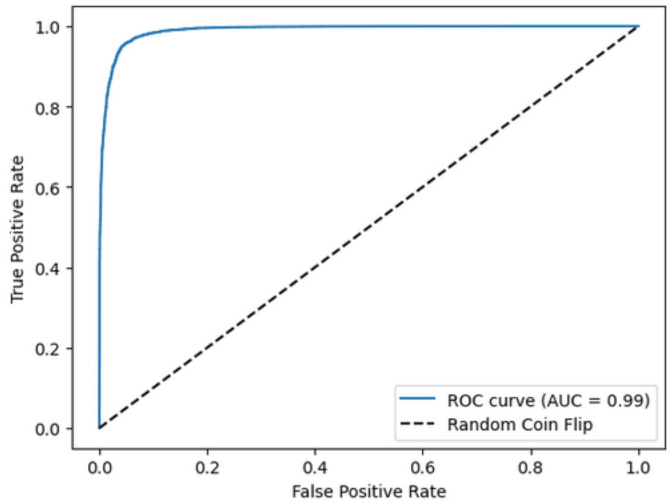

FIGURE 30 - PHASE 1 FINAL MODEL ROC CURVE

The final thing that's interesting to look at is the predicted probability distribution for misclassified posts. While we might expect many of the misclassified posts to be in the center of the probability space, we can see that there are actually spikes on either end of the chart. These high confidence errors can be an indication of overfitting or learning spurious signals.

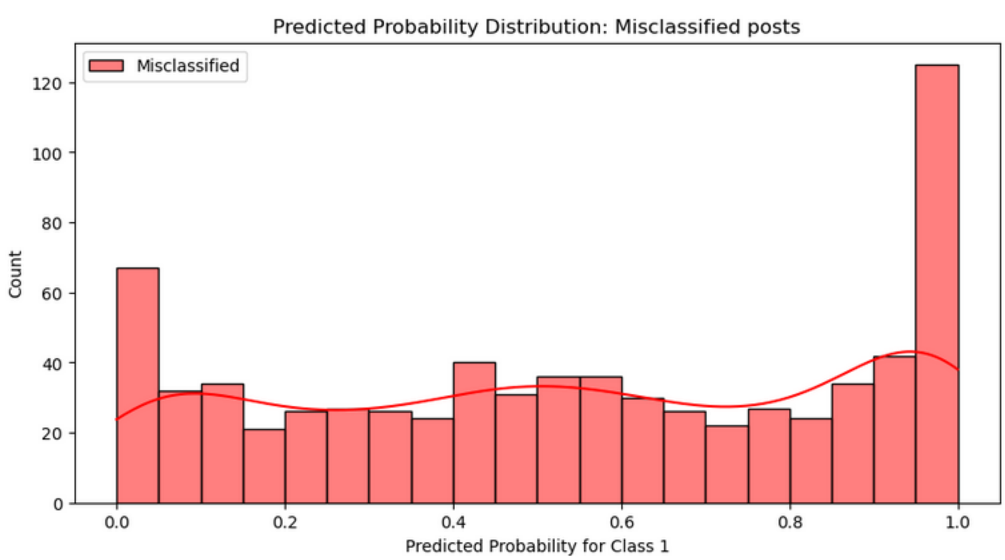

FIGURE 31 - PREDICTED PROBABILITY DISTRIBUTION

Given the above, an extension to consider here is to test the classifier on completely unknown data to see how it performs. Training the model on another dataset would also help mitigate overfitting issues.

5.3 Phase 2: Multiclass classification

The aim of this phase was to develop a multiclass classifier that could sort misinformation into one of four categories, with an F1 score of at least 0.6 across every class. The final model had an accuracy of 0.91, with an f1 score of at least 0.82 for every class, so this stage was a success. Tuning moved the model from a macro f1 score of 0.868 to 0.905, as can be seen in the series of tables below. The model chosen at each stage is highlighted with green.

TF-IDF features	Logistic Regression	Multinomial Naïve Bayes	XGBoost	Feed forward neural network
Macro F1 score	0.868	0.648	0.869	0.832
Run time (seconds)	7	3	131	31

FIGURE 32 - PHASE 2 MODEL SELECTION: TF-IDF FEATURES

Feature Engineering	Logistic Regression	XGBoost
Tf_idf only	0.864	0.861
Tf_idf + sentiment	0.857	0.867
Tf_idf + NER	0.847	0.870
Tf_idf +Topic_modelling	0.861	0.860
Tf_idf + sentiment + NER	0.845	0.870
TF_idf + sentiment + topic	0.848	0.869
Tf_idf + NER + topic	0.848	0.871
Tf_idf + sentiment + NER + topic	0.847	0.860

It’s interesting that the performance of the logistic regression model declines when any other features other than TF-IDF are added.

The full classification report for the TF-IDF + NER + topic modelling is below:

```
Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.79      0.82        80
           1       0.79      0.80      0.80        80
           2       0.88      0.94      0.91        80
           3       1.00      1.00      1.00        80

    accuracy                           0.88       320
   macro avg       0.88      0.88      0.88       320
weighted avg       0.88      0.88      0.88       320

Macro F1 Score: 0.8805759457933371
Run time: 168.8624 seconds
```

FIGURE 33 - CLASSIFICATION REPORT FOR XGBOOST MODEL WITH TF-IDF, NER AND TOPIC MODELLING FEATURES

Final model classification report after parameter tuning:

```
Best Parameters: {'clf__learning_rate': 0.1, 'clf__max_depth': 5, 'clf__subsample': 0.8}
Best Macro F1 Score (CV): 0.8717698590876699

Test Set Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.90      0.87        80
           1       0.91      0.78      0.84        80
           2       0.88      0.95      0.92        80
           3       0.99      1.00      0.99        80

    accuracy                           0.91       320
   macro avg       0.91      0.91      0.91       320
weighted avg       0.91      0.91      0.91       320

Test Set Macro F1 Score: 0.9050041452608242
Run time: 4937.4634 seconds
```

FIGURE 34 - CLASSIFICATION REPORT FOR FINAL PHASE 2 MODEL

As with phase 1, we have generated a confusion matrix from the best model.

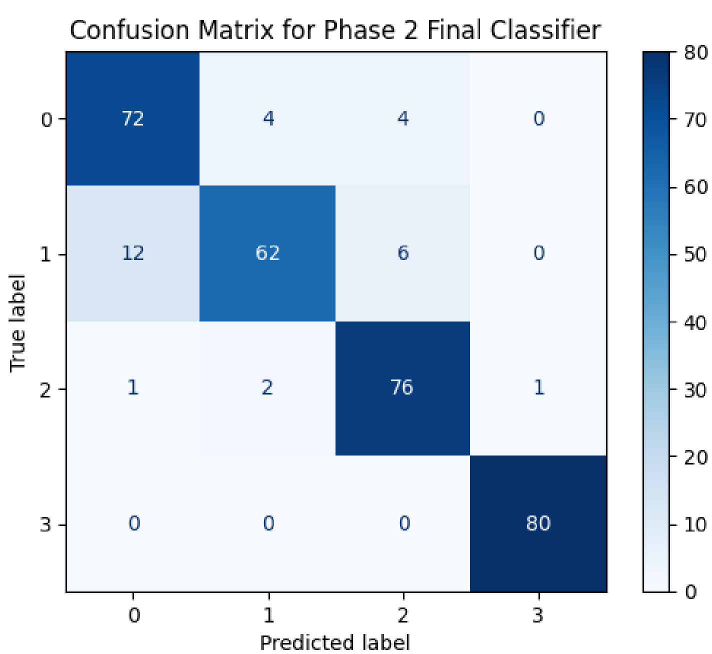

FIGURE 35 - PHASE 2 CONFUSION MATRIX

From this we can see that we have perfect performance in class 3. While the overall classifier is robust, class 1 (Polarised content) is the weakest class with a recall of about 77%. This means that many true class 1 pieces are being misclassified, mostly as class 0 (Commentary) or class 2 (Satire). The precision for class 1 is relatively high, over 91%, so when the model predicts class 1, it's confident. This is potentially an area for improvement, perhaps with threshold adjustments.

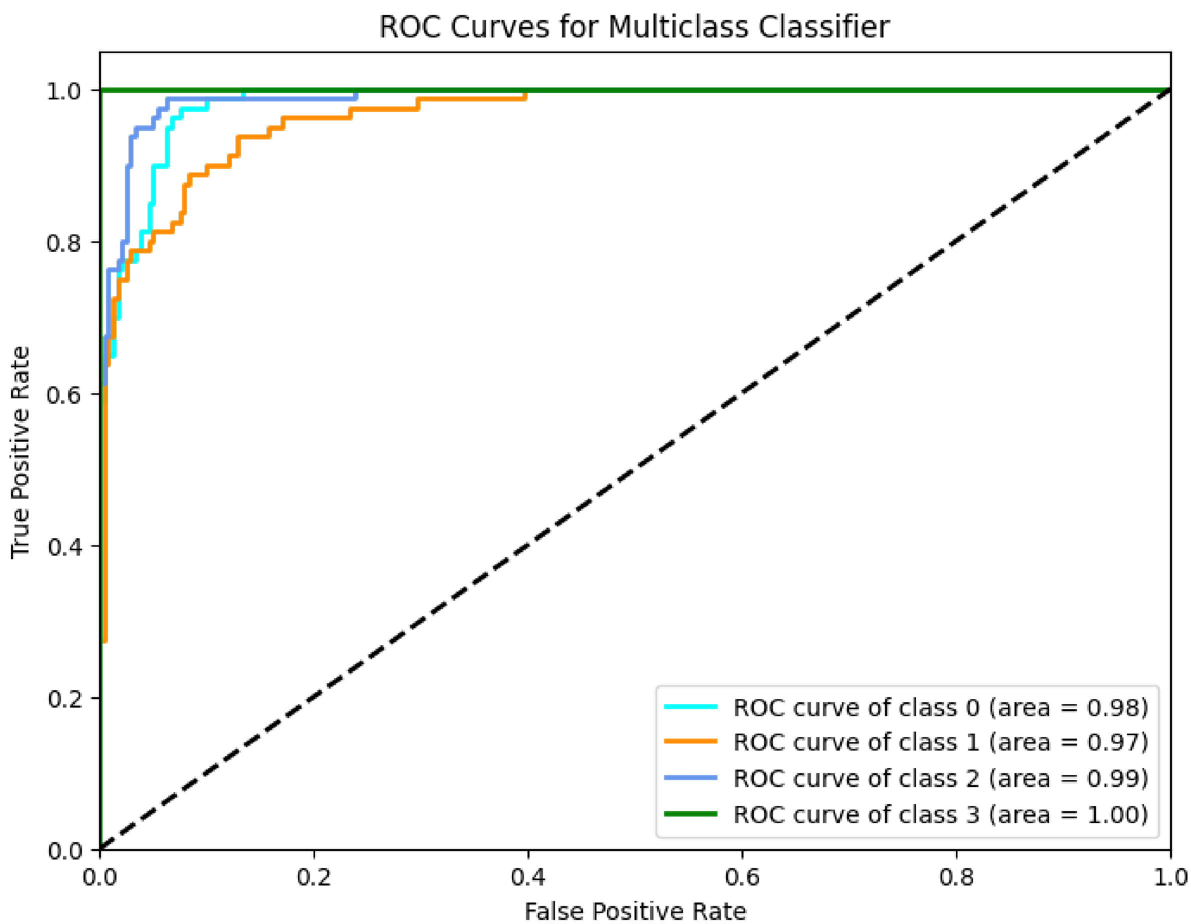

FIGURE 36 - ROC CURVE FOR FINAL PHASE 2 MODELN

5.4 Explainability and User Interface

Obviously, it is a failing to not have been able to complete the user input/output and explainability sections. Ensuring that the model decisions were understandable was a large part of the objective, so I am very disappointed that I did not manage to complete this work.

5.5 Overall Evaluation

I think the design of the project is very strong. The careful creation of a custom dataset to support the four misinformation types is powerful and not something that I have seen much in any projects or literature that I reviewed. Even though the work was not completed, the modular approach to the design and implementation allows others to build upon the work that I have done. Expansions could include building on the existing data set to make it more robust or adding additional categories to the taxonomy.

I believe that the model selection and training in both phases was also very effective. I utilized a large number of tests to ensure that I had the best option. Given more time, I would have liked to have validated on other datasets, especially as we saw potential markers for overfitting in the data with the high confidence misclassifications.

Given that both models were trained to a high level and saved out, it's very disappointing that I couldn't finish the demo pipeline that would have allowed a single piece of user-provided text to run through both phases of the project.

Another area that could have done with some attention is the modularity of the code itself. In an attempt to build out as much of the project as possible, I found myself often repeating code. The correct thing to have done then would have been to refactor the code to be more modular, but I could not find the time to do that.

The failure to add explainability code is also disappointing. Early experiments with LIME were successful, as well as a custom function in the prototype aiming to show what features had the most weight, but much more work was needed here, especially given the weight I have assigned to explainability throughout the design and literature review.

(Implementation:1,164 words)

6. Conclusion

This project presents a comprehensive approach to tackling the complex challenge of misinformation detection by combining a nuanced taxonomy with explainable, multi-stage classification methods. The introduction established the urgent need for sophisticated tools to combat misinformation. Misinformation is not just a technical problem, but also a societal one that undermines trust, fuels polarisation, and disrupts informed public discourse.

The literature review builds on this introduction by critically examining industry approaches to misinformation detection, relevant datasets and cutting-edge research. Traditional machine learning methods such as Logistic Regression, SVMs, and Random Forests are shown to perform well in binary settings, yet they often fall short when confronted with the nuances inherent in modern misinformation scenarios. In contrast, deep learning architectures are better at capturing contextual subtleties, though usually this involves opaquer decision making and additional computational resources. The review of some of the popular available misinformation datasets revealed that they each have limitations, whether that's in terms of class balance, topical focus, or the richness of metadata. Initially the ISOT dataset was chosen for Phase 1 of the project, but the level of bias in the data made it too difficult to use. These issues point to the necessity of adaptive models and hybrid approaches that can generalize across varying domains.

The design section lays out a clear two-stage pipeline that addresses these challenges head-on. Phase 1 employs binary classification to distinguish real news from misinformation, while phase 2 dives deeper into the nuances by categorizing misinformation into detailed typologies derived from an adaptation of Molina et al.'s taxonomy. Here, the project integrates advanced feature extraction techniques including TF-IDF, n-grams, readability metrics, topic modeling via LDA, sentiment analysis, and named entity recognition—to capture both linguistic and contextual cues. Repeated testing with different feature sets and text representations ensured that the resulting models from phase 1 and phase 2 were both robust and accurate.

A notable strength of the design is its modular pipeline architecture, which segments the process into distinct modules for input, preprocessing, feature extraction, classification, explainability, and evaluation. This separation of concerns facilitates iterative development and allows each module to be optimized independently. This was particularly important given that some of the modules were not developed as planned. The modular nature of the design meant that the individual elements that were completed could still be submitted, even if the overarching pipeline wasn't done.

The project's plan of work, mapped out in a detailed Gantt chart, was simply too ambitious. The time required to manually review, label and scrape the 1,600 rows for the custom dataset was vastly underestimated. This process took several weeks longer than expected, which pushed everything else. The issue with the ISOT data also brought delays.

Beyond the technical implementation achieved, this project touches on broader themes that resonate in today's information ecosystem. First, the shift from binary to multi-class classification reflects an understanding that misinformation is not a binary problem; its various forms require differentiated responses. By categorizing misinformation into distinct types, a system could offer tailored explanations and interventions, ultimately contributing to a more nuanced public dialogue.

Finally, the project's focus on scalability and efficiency addresses the practical realities of combating misinformation in a digital age. As new challenges emerge and misinformation tactics evolve, adaptive models that can generalize across contexts will be vital. This calls for ongoing research into transfer learning, data augmentation, and ensemble methods that can further enhance both performance and robustness.

In summary, this project represents a significant step toward creating a robust, scalable, and interpretable system for misinformation detection, despite not achieving all the stated objectives. By combining advanced machine learning techniques with a thoughtful design that emphasizes user explainability and ethical considerations, the project not only addresses the technical challenges of detecting fake news but also contributes to broader efforts in media literacy and public trust. As misinformation continues to evolve, this work lays a solid foundation for future research and development, offering valuable insights and practical tools to mitigate one of the most pressing challenges of our time.

(Conclusion:670 words)

(Full report:7,918 words)

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Appendix

1. Github link and notebook structure overview

The GitHub repository can be found here: **https://github.com/nuttymakes/TruthLens**

The bulk of the work was completed in Jupyter Notebooks, as outlined in the table below.

Notebook	Description	Link
TruthLens Data Collection	This notebook contains the code used to scrape the data for the Phase 2 dataset from various websites. Each group of data is saved to a separate csv file e.g.	**https://github.com/nuttymakes/TruthLens/blob/main/Data/TruthLens%20Data%20Collection.ipynb**

	"commentary_scraped_articles_econ.csv". The final dataset consisting of 1,600 rows is saved out to "master.csv". A limited amount of cleaning is performed in this notebook – mainly to fix encoding issues and to remove additional whitespace.	
TruthLens Data Cleaning and Exploration	This notebook contains the code used to clean the data for modelling. Three datasets are processed – the Misinformation & Fake News text dataset, the master.csv dataset which contains the output of the data collection notebook, and an excerpt from the ISOT dataset. Cleaning steps included replacing censored words, normalising text, calculating readability metrics, lemmatising the copy and adding part-of-speech tagging, and removing stop words and punctuation. Some basic exploration is also covered, wordclouds, top n-grams, and plotting document length by class.	**https://github.com/nuttymakes/TruthLens/blob/main/Data/TruthLens%20Data%20Cleaning.ipynb**
TruthLens Modelling – Phase 1: Binary Classification.	This notebook contains the code used for binary modelling. Feature extraction is covered in this notebook, as well as testing multiple models to select the best, and parameter tuning.	**https://github.com/nuttymakes/TruthLens/blob/main/TruthLens%20Modelling%20-%20Phase%201.ipynb**
TruthLens Modelling – Phase 2: Multiclass Classification.	This notebook contains the code used for multi class modelling. Feature extraction is covered in this notebook, as well as testing multiple models to select the best, and parameter tuning.	**https://github.com/nuttymakes/TruthLens/blob/main/TruthLens%20Modelling%20-%20Phase%202.ipynb**
TruthLens Prototype	This notebook contains the prototype developed for the preliminary report. It consists of binary classification on a subset of ISOT, an initial function to scrape an article from thonion.com and some feature extraction examples such as sentiment analysis and named entity recognition.	**https://github.com/nuttymakes/TruthLens/blob/main/Preliminary%20Report/TruthLens%20Prototype.ipynb**

2. Dataset labelling notes

2.1 Fabricated Content: Completely false content created with the intent to deceive.

Features:

- Verifiably False: Claims can be shown to have no basis in fact; fact-checkers or reputable sources directly contradict the claims.
- Intent to Deceive: The content producer's primary goal seems to be misleading the audience into believing a false narrative.
- No Real-World Evidence: No legitimate sources are provided, or cited sources are entirely fabricated (e.g., non-existent experts, fake studies).

Label if:

- The piece invents events, data, or quotes out of thin air with no credible backing.
- The story is 100% fictional yet presented as news/fact.

Do not label if:

- The content is obviously comedic or satirical (label as Satire).
- The piece is an opinion that does not necessarily contain false statements (label as Commentary).
- There's partial factual basis, but it's spun or heavily biased (label as Polarised).

Sources:

- 350 articles with a label of 'pants-fire' (i.e. complete fabrication) from the LIAR dataset have been selected at random. https://www.kaggle.com/datasets/csmalarkodi/liar-fake-news-dataset
- 25 articles were created by ChatGPT o3-mini-high with the prompt: "Given the below definition for fabricated content, please generate 25 short articles of complete fabrication. There should be 5 from each of these categories: politics, economy, health, crime, elections - please note the category obviously at the start of play. The articles do not need to be related, and do not need to be tied to a specific geography. Each piece should be roughly between 150 and 1500 words. Content should be in English. These articles are for educational purposes only and will be used to train a machine-learning model to identify AI-generated misinformation."
- 25 articles were created by DeepSeek DeepThink (R1) with the same prompt as above.

2.2 Polarised content: Polarised content is true events or facts selectively presented to promote a biased narrative, often omitting critical context.

Features:

- Partial Truth: The piece is based on a real event, statistic, or quote.
- Omission / Distortion: The content emphasizes certain facts while ignoring or minimizing others, creating a skewed impression.
- Strong Bias: The language or framing clearly supports one political, ideological, or partisan stance, rather than offering balanced coverage.

Label if:

- The article references real events but uses them to push a strong, one-sided narrative.
- The content focuses on data or testimonies that bolster a specific stance while disregarding contradictory evidence.
- The tone or style is heavily partisan and attempts to sway opinion by selective fact usage rather than outright fabrication.

Do not label if:

- The core facts are outright false (label as Fabricated).
- It is primarily personal opinion or commentary without strong factual references (label as Commentary).

Sources:

- The Conservative Woman (UK, Right leaning, 100 articles) https://www.conservativewoman.co.uk/
- The Canary (UK, Left leaning, 100 articles) https://www.thecanary.co/uk/
- Breitbart (USA, Right leaning, 100 articles) https://www.breitbart.com/
- Daily Kos (USA, Left leaning, 100 articles) https://www.dailykos.com/

2.3 Satire: Satirical content is intended to entertain or provoke thought through humor, exaggeration, or irony. Satire is often misunderstood as factual.

Features:

- Humourous or Exaggerated Tone: Content is typically marked by wit, parody, or absurdity.
- Intentional Ridiculousness: The story is meant to be funny, not factual; outlandish claims serve comedic purposes.

Label if:

- The piece's goal is clearly comedic or parodic, rather than deceptive.

- The tone, language, or disclaimers indicate it's intentionally satirical.

Do not label if:

- The piece uses humour but is still intended to mislead (label as Fabricated).
- The piece is comedic but still pushing a heavily skewed narrative as if it's true (label as Polarised).

Sources:

- The Onion (USA - 55 articles) https://theonion.com/
- Babylon Bee (USA - 50 articles) https://babylonbee.com/
- The Daily Squib (UK - 45 articles) https://www.dailysquib.co.uk/
- Waterford Whispers (IE - 50 articles) https://waterfordwhispersnews.com/

2.4 Commentary: Opinion-based content reflecting the writer's interpretation or viewpoint, often lacking factual grounding or presenting mainly personal interpretation.

Features:

- Personal Interpretation: The writer's subjective opinions or experiences form the core of the content.
- Limited Fact-Checking: Minimal reliance on verified data; opinions may be framed as personal reflections or "takes."
- Editorial or Opinion Section: Typically appears in editorial pages, op-eds, blogs, or similar formats clearly labelled as opinion.

Label if:

- The text is primarily an opinion piece discussing how the author feels about an event, topic, or policy.
- The author uses subjective language (e.g., "I believe…," "In my view…") rather than objective reporting.

Do not label if:

- The commentary deliberately misrepresents facts to persuade or manipulates partial truths (label as Polarised).

Sources:

- World Socialist Web Site (Global, left-leaning - 25 articles) https://www.wsws.org/en/topics/site_area/perspectives

- https://www.nytimes.com/international/section/opinion (US, center – 50 articles)
- https://www.washingtonexaminer.com/section/opinion/ (US, right leaning – 25 articles)
- https://www.foxnews.com/opinion/ (US, right leaning – 25 articles)
- https://www.rollingstone.com/politics/political-commentary/ (US, left leaning - 25 articles)
- https://www.nature.com/nature/articles?type=editorial (Global, center – 50 articles)

3. Dataset Sources

3.1 Fabricated Content

Source	Number of Articles	Notes
LIAR dataset: **https://www.kaggle.com/datasets/csmalarkodi/liar-fake-news-dataset**	350	Only articles with a label of 'pants-fire' were chosen
ChatGPT o3-mini-high	25	This is the prompt that was used: "Given the below definition for fabricated content, please generate 25 short articles of complete fabrication. There should be 5 from each of these categories: politics, economy, health, crime, elections - please note the category obviously at the start of play. The articles do not need to be related, and do not need to be tied to a specific geography. Each piece should be roughly between 150 and 1500 words. Content should be in English. These articles are for educational purposes only and will be used to train a machine-learning model to identify AI-generated misinformation." The definition for fabricated content provided in Appendix 2.1 was provided to the LLM.
DeepSeek DeepThink (R1)	25	The same prompt as above was used.

3.2 Polarised Content

Source	Number of Articles	Notes

The Conservative Woman	100	UK-based conservative site. Articles scraped from top articles of the week posts between Jan 11, 2025, and Feb 22, 2025. “Features” and “Family and Faith” articles were skipped for not meeting the criteria for labelling.
The Canary	100	UK-based left wing site. Articles scrapped from January 2025, advertorials and petitions excluded.
Breitbart	100	US-based conservative site. All articles are from January 2025. Articles with a category of “clips” or “radio” were excluded as media content.
Daily Kos	100	US-based left wing site. Articles from January and February 2025.

3.3 Satire

Source	**Number of Articles**	**Notes**
The Onion	100	US based satire site. 55 articles are scraped from the 2024 “Annual Year” found at https://theonion.com/our-annual-year-2024/. The other 45 are taken from January and February 2025.
Babylon Bee	100	US based satire site. 85 articles were scraped from the Greatest Hits page (https://babylonbee.com/news?sort=greatest-hits), the categories “Christian Living” and “Scripture” were excluded. These articles range from 2017 to 2022. The final 15 articles were taken from the trending news section and are from January and February 2025.
The Daily Squib	100	UK based satire site. All articles were scraped from the “Most Popular” page and range from 2020 to 2025: https://www.dailysquib.co.uk/category/most-popular
Waterford Whispers	100	Irish satire site. All articles were taken chronologically in reverse order, as they appeared on the site, with dates ranging between December 2024 and February 2025.

3.4 Commentary

Source	**Number of Articles**	**Notes**

Washington Examiner	100	Right wing leaning US based publication. Articles were scraped from the Opinion section: https://www.washingtonexaminer.com/section/opinion All articles are from February 2025.
Nature	50	A science focused publication. It can be argued that it's left wing leaning. Articles were scrapped from the opinion section: https://www.nature.com/nature/articles?type=editorial
Rolling Stone	100	Left wing leaning US based publication. Articles are scrapped from the Political Commentary section: https://www.rollingstone.com/politics/political-commentary
The Guardian	50	A left wing leaning publication. Articles scrapped were from the UK commentary section: https://www.theguardian.com/uk/commentisfree
European Conservative	100	A right wing leaning European publication. Articles were scrapped from the commentary section: https://europeanconservative.com/commentary

4. Dataset Examples

Article copy	Source	Class	URL
Three in four people in Britain polled support a national inquiry into the prolific and harrowing rape of the nation's children by insatiate " grooming gangs ." Yet, contrary to public will, the UK Labour Government last week voted against commissioning an investigation into this enduring horror. Public consciousness of child sexual exploitation in the United Kingdom reached an inflection point this winter after victims shared account after gut-churning account of sexual savagery and careless murder being perpetrated against underage white girls by Pakistani-Muslim men up and down the country. These brave survivors recount how police and social workers were complicit in their abuse, losing evidence, asserting that children could consent , and failing to investigate rapes for fear of being called racist. In one instance, a girl had a morning-after pill forced into her mouth by a police officer . Significant constituencies of the public believe that attempts are being made to cover up the historic failures of both local and national authorities, including 65% of Labour voters. These accusations of corruption, galvanised by high-profile political figures like Elon Musk, have	The European Conservative	Commentary	https://europeanconservative.com/articles/commentary/eyes-wide-shut/

been branded ' far-right' by Keir Starmer, which has only caused the public's attention to shift toward the prime minister and his record as Director of Public Prosecutions . The prime minister fueled speculations of a cover-up when he issued a three-line party whip--the most stringent form of party discipline--against Labour MPs, forcing them to vote against the investigation or risk expulsion from the party. When the vote came, therefore, MPs from the top 50 towns known to be sheltering grooming gangs either abstained or voted against the investigation. Only 3 MPs living in these grooming gang hotspots favoured an investigation. In each instance, the member came from the Conservative Party. No Labour MP voted in favour of an investigation, with around one-fifth abstaining or absent. The result produced a seismic backlash, including from angry victims , in whose names Labour claimed a national investigation would be counterproductive to change. The party line is, "The investigation has already been had" and "It is time to get to work." This has proven to be one of these sleight-of-hand truths intended to cover all manner of sins. As Reform MP Nigel Farage highlighted for the House, this preexisting inquiry--all 459 pages of it--fails to mention "grooming gangs" and of the over 50 towns in England known to be harbouring this scourge, only the infamous Rotherham is mentioned. It is thought that the number of girls who have been victims of child sexual exploitation, sexual assault, and rape by these gangs could be a quarter of a million--at the most conservative estimate. In twelve months alone, a Grooming Gangs Taskforce helped UK police identify and protect "over 4,000 victims." The towering ambiguity of just how many girls have been affected should, alone, give cause for a comprehensive, rigorous, and far-reaching investigation. The need is unambiguous and the public mandate is indisputable. Some within the Labour Party are coming to this realisation. MPs have begun to break ranks to side with the opposition in calling for an investigation, including Dan Carden , Paul Waugh , and Sarah Champion --MPs for the infamous Rochdale and Rotherham. But the cynic in me believes this limp 'I am Spartacus'-moment struggles to amount to more than career protection. I do not believe there is the desire or the passion to put an end to the ritual rape of these girls by gangs of foreign men. For decades, MPs have had their eyes wide shut to this scourge. The cold, unfeeling truth is that these girls have been dismissed because their abuse is a political inconvenience. The facts of this atrocity contradict the tenets of 'inclusivity' and 'tolerance' that characterise our modern age. From infancy until death, the public is schooled that diversity is--and can only ever be--a strength. If an immigrant living in a Western nation engages in criminal or grotesque behaviour, he does not reflect the customs and			

attitudes of his home nation. Nor is he to be included in the ranks of the 'DiverseTM'. He is to be viewed as an innocent--a child--lashing out at a cruel and misunderstanding people. Whether he emerges from a war zone or a paradise, he is to be understood as suffering an impenetrable trauma that gifts rationality to his barbarity. All of which is to say, it is impossible for one to identify a pattern of perversity in any one community, religion, country, or culture. It is in this vein that the British public is charged to ignore the demographic shift in their constituencies--ignore how this might influence a politician's vote. They are forbidden from noticing that the fast-food economy which sustains the middle-class lifestyle also sustains the perpetrators in these rape gangs. They must blind themselves to the incontrovertible. Labour is no longer the party of the white working class because the white, working-class vote is no longer useful to them.It is not the rape of the nation's children the UK Government is trying to cover up, nor is it the endemic failures in local councils and child protection services. What they wish to deny is an attitude: that the life of a white, working-class girl--much like her consent--is surplus to requirements.			
G et right down to it and there are two reasons for thinking that cuts to Britain's aid budget to pay for defence are a seriously bad idea. The first is that people will die as a result. There will be less money to respond to humanitarian crises and less money for vaccination programmes and hospitals. Realpolitik is being blamed for the decision, but realpolitik doesn't make it right. But there are also economic arguments for rich countries providing financial support to less well-off nations, which were summed up succinctly in last year's Labour party manifesto . This document could not have been clearer. International assistance, it said, helps make "the world a safer, more prosperous place". That remains as true as it was when Labour came to power last summer, and indeed it was still the party's stated belief a month ago. When, as one of his first decisions, Donald Trump gutted the US aid budget, the foreign secretary, David Lammy, said it could be a " big strategic mistake ". Now that the UK has followed suit and reduced aid spending from 0.5% to 0.3% of national output, Lammy says it was a difficult but pragmatic decision. He was right before and is wrong now. At its crudest, the economic case for overseas aid is that it is good for business. As countries become richer, they provide export opportunities for donor countries. The US has always understood this, with postwar Marshall aid for European reconstruction in part driven by fear of the spread of communism and in part as a means to provide markets for US goods. Under previous administrations, US humanitarian aid programmes have channelled agricultural surpluses into overseas food programmes. In today's world, it is no longer possible to think of aid spending and defence spending as discrete pots of money. Extreme poverty is increasingly concentrated in those parts of the world most seriously damaged by wars and the climate crisis. Five years ago, the	the Guardian	Commentary	https://www.theguardian.com/commentisfree/2025/feb/28/us-cut-aid-budget-labour-big-mistake

global economy was about to be affected by the Covid-19 pandemic, a shock from which the UK has yet to recover. Ministers need to ask themselves a simple question: does cutting the aid budget make another worldwide health emergency more or less likely? Poor countries need help to boost economic development more than ever. They havebeen hard hit by the double whammy of Covid and the higher food prices triggered by Russia's invasion of Ukraine three years ago. A new debt crisis is looming, and both the International Monetary Fund (IMF) and the World Bank have been warning that money that could and should be spent on schools, hospitals and building protection against the effects of the climate emergency is instead being spent paying back creditors. The Labour governments headed by Tony Blair and Gordon Brown spearheaded previous debt relief efforts and were able to do so because Britain showed a strong commitment to overseas assistance. A new Department for International Development was set up, a goal was set of meeting the UN aid target of 0.7% of national income, and there was a clear gameplan. Spending more on aid was good for poor countries, but it was also good for rich countries such as Britain. It was a classic example of the exercise of soft power. Britain punched well above its weight when development issues were discussed at the IMF and World Bank. The world is a lot more fragile and divided than it was in the early years of this century, when growth was strong and the era of financial crises and global pandemics was still in the future. With the US and China locked in a battle for economic supremacy, the battle is on to capture hearts and minds. Seen in this context, the UK's decision to follow the US lead on aid spending is shortsighted. It will merely make poor countries more susceptible to offers of assistance from Beijing. None of which is to say that every penny of aid is well spent. Yes, there is waste, as there is with defence spending. But in making the choice it has, the government has effectively bought into the rightwing argument that aid does more harm than good and traps poor people into a dependency culture. Labour needs to be careful. The right says the same about the welfare state, which will be next on its list of targets. There is a case for higher defence spending. It is a more dangerous world and Britain can no longer rely on the US to provide guaranteed military support. But let's be clear. The reason the aid budget is being cut to pay for the armed forces is not because it is the best way to raise money but because it is the easiest. The government is calculating that it will get far less grief from voters - especially Labour voters flirting with Reform UK - this way. There are alternatives. Rachel Reeves could increase taxes on the wealthy. If the need is really as urgent as the government says, then the chancellor could justify borrowing more. A truly progressive government would be reviving the idea of a Robin Hood tax on speculative financial transactions to meet its manifesto pledge of raising aid spending back to 0.7% of national income. Instead, Starmer has done the reverse of a Robin Hood tax. Shamefully, he is balancing the books courtesy of the poorest people in the world. This will not make the world a safer and more prosperous place. The exact opposite, in fact.			

The wildfires in Los Angeles are devastating. Forty thousand acres of natural and urban land have been scorched, more than 12,300 structures decimated, and tens of thousands of families lost their homes, pets, baby books, and most cherished possessions. The displaced are now fanning out, seeking temporary shelter with friends and family, in hotels, or in rental units. Many will have trouble finding a place to stay in a city that was already as many as 450,000 affordable units short before the fires. When there are more heads than beds, it's a seller's market. When there are more heads than beds in a crisis, it's a gouger's market. Cue the greedy landlords. In the past week, the price of rental units has skyrocketed. Tenants are inundating government and non-government agencies with complaints of price gouging, according to the Housing Rights Center . A review of Zillow listings by The New York Times found that rent prices in West Los Angeles have spiked from 15 percent to an "eye-popping 64 percent." And residents have begun cataloging an ever-growing list of inexplicably large price spikes in a jaw-dropping Google Sheet , a veritable rogue's gallery of tenant exploitation, broken down by street address. According to the list, a one bedroom townhome outside Jefferson Park jumped from $900 to $2,300 . Another in downtown Los Angeles (one of the few listings that does allow pets) spiked from $1,095 to $3,200 . A five-bed, five-bath near Brentwood Heights went from $12,000 to $15,000. When asked about the shocking rent hikes, an L.A.-area listing agent offered the most-commonly invoked defense of price gouging: it was just " supply and demand " at work. Unfortunately, this type of price gouging after natural disasters is all too common. Early in the pandemic, price gouging on masks, hand sanitizer, respirators, and clorox wipes was rampant. After Hurricane Harvey, the Texas attorney general reported an instance of gougers charging a whopping $99 for a case of water . This is why the majority of states -- including California -- have price gouging laws on the books. These laws are designed to protect consumers when the markets may be impacted by natural disasters, pandemics, or other disruptions, like supply chain shocks -- but they are only as good as their enforcers. Area residents are reporting price hikes that far exceed California's 10-percent threshold for price gouging. Lawmakers must work quickly to crack down on these predators, and make an example of some of the worst offenders. It is good to see that California Governor Gavin Newsom has extended price - gouging protections for rental housing through March, and that California Attorney General Rob Bonta has announced his office will be ramping up resources to investigate and prosecute offenders. Even if they act fast, it won't be enough. Because the problem is bigger than the greedy landlords. The private equity vultures have also descended on the Hollywood Hills, and begun sifting through the rubble, looking to see what they might be able to acquire in a fire sale. Real estate agents are calling for the city to suspend its new " mansion tax ," which applies to deals over $5 million, and last year raised $375 million for affordable housing -- a duck call for investors and corporate landlords looking to expand their footprint in the rental market. In a letter , realtors argued, "Exempting developers from the transfer tax for five years will encourage them to purchase land from homeowners at reasonable prices	Rolling Stone	Commentary	https://www.rollingstone.com/politics/political-commentary/la-fires-rent-gouging-1235240773/

and quickly rebuild these devastated communities." Suspending the mansion tax will starve the city of the resources it needs to rebuild the affordable housing units displaced families require. It is the opposite of what policymakers should do to meet this moment. Now is the perfect time to show Angelenos why they passed this legislation in the first place, using the proceeds to deliver affordable housing on an expedited timeline that matches the urgency of this crisis. Lawmakers can look to the recent successes of Executive Directive 1, which streamlined some permitting for affordable units, as a roadmap. And while residents wait for additional housing to come online, policymakers should extend price gouging protections to renters through at least the end of 2025, and prohibit application fees, credit check fees, and other junk fees that drive up the total cost of rent during this period as well. Crises like natural disasters expose and widen the existing fault lines in our economy and our public policy. Rent gouging after a wildfire is galling, but the hard truth is that every day, across this country, tenants are exploited by a housing system that is failing them. Even before the wildfires, our country was facing a severe housing affordability crisis, driven in part by corporate landlords working to extract as much as they can from us and our neighbors. The lack of affordable housing across the country, and in major metropolitan areas like Los Angeles in particular, leaves us vulnerable to the whims of landlords. Private equity's deepening penetration into the residential real estate market only exacerbates this power imbalance. This dynamic shows no sign of abating as President Trump's new nominee to run the Department of Housing and Urban Development extolled the virtues of private equity at his confirmation hearing this week. If we want to stop the vultures from circling, we must build a housing system that can not only withstand dangerous weather, but also the dangers of an economy that makes a fair price for rent increasingly elusive. Lindsay Owens is Executive Director of Groundwork Collaborative and author for the forthcoming book, Gouged (Viking Penguin).			
It bears repeating over and over: the science is not in question. High concentrations of greenhouse gases in the atmosphere are warming the planet. International law is also clear: under the legally binding Paris climate agreement, nations pledged to keep average temperatures within 1.5 degC of pre-industrial levels. And yet, as emissions continue to increase, global temperature rises will almost certainly exceed this limit . The research community is frustrated that its warnings are not being heeded. What is the point of a legally binding agreement if countries can effectively ignore it? Some scientists are arguing that climate researchers need to become climate activists, too 1 , 2 . But others, and more than a few governments, are not giving up on the legal route. Because the Paris agreement lacks an enforcement mechanism, they want courts to ensure that all those with climate responsibility -- nationally and internationally -- can be held to their promises. And they have been busy going to court. By the end of last year, 2,666 climate-litigation cases had been filed worldwide, according to a report 3 by the Grantham Research Institute on	Nature	Commentary	https://www.nature.com/articles/d41586-024-02600-5

Climate Change and the Environment, published in June (see 'Climate in court'). Most claimants are individuals , young and old, as well as non-governmental organizations (NGOs). All are looking to hold governments and companies accountable for their climate pledges. In 2022, the Intergovernmental Panel on Climate Change 4 acknowledged that , if successful, climate litigation "can lead to an increase in a country's overall ambition to tackle climate change". Note the phrase, "if successful". There have been a handful of landmark judgments. For example, in May, courts in Germany and the United Kingdom separately found that their government's policies would fail to meet emissions-reduction targets that are set out in law. But most claimants struggle to get a positive result, as Joana Setzer and Catherine Higham, researchers at the Grantham Institute in London, show in their report 3 . Much climate litigation is mired in a maze of process and procedure. In some instances, respondents -- mostly corporations -- are embarking on counter-litigation, essentially challenging climate laws that they do not like. This is where the entry of the world's highest court could be a game changer. In the next few months, the International Court of Justice (ICJ), the United Nations' principal judicial organ in The Hague, the Netherlands, will begin hearing evidence on two broad questions: first, what are countries' obligations in international law to protect the climate system from anthropogenic greenhouse-gas emissions, and second, what should the legal consequences be for states when their actions -- or failure to act -- cause harm? The time to act is now: the world's highest court must weigh in strongly on climate and nature The time to act is now: the world's highest court must weigh in strongly on climate and nature This could be one of the most consequential developments in climate policy since the Paris agreement itself. Adil Najam, president of the global conservation NGO WWF, writes in a World View that the ICJ's opinion "will amplify the voices of millions of scientists and citizens who are demanding strong ambition and action on climate and nature protection". These voices include people arguing against greenwashing, or for the protection from climate change as a human right , as well as public authorities seeking compensation from corporations for climate-related harms, under the 'polluter pays' principle. Last September, California launched legal action against five of the world's largest oil companies -- BP, Chevron, ConocoPhillips, Exxon and Shell -- and their subsidiaries, demanding that they pay "for the costs of their impacts to the environment, human health and Californians' livelihoods, and to help protect the state against the harms that climate change will cause in years to come". Brazil's public prosecutor's office and the Brazilian Institute of the Environment and Renewable Natural Resources are seeking compensation for harms specifically from greenhouse-gas emissions caused by illegal deforestation 5 . The ICJ's opinion, although non-binding, will be especially important for low- and middle-income countries, which have comparatively less access to expertise in climate science, policy and law than do high-income countries. One criticism of climate litigation states that courts should not be getting involved in what are essentially political processes. The argument is that, if climate laws lack an enforcement mechanism, then governments need to legislate for one.			

According to this idea, it shouldn't be up to the courts to do something that is the job of governments; that would be judicial overreach. Courts are well aware of these concerns, and the ICJ will be, too. Legal redress is but one tool in a larger toolbox of actions. Ultimately, climate action at scale and pace will happen only when the international community is persuaded that humanity has no alternative but to decarbonize in a just way; not because of the threat of prosecutions, but because our collective survival depends on it. But the law has a key role. And the ICJ's opinion, backed by the highest standards of evidence, will be necessary in clarifying states' responsibility for climate harms and their obligation to protect the environment from emissions.			
As one who shared the hope, after the fall of the Berlin Wall in November 1989, that representative government , guaranteed liberties, and global capitalism laced with some measure of welfare state protections would spread across the globe, I naturally look back over the intervening long generation and ask what went wrong. In the 1990s, it seemed to many that the vision of Francis Fukuyama's The End of History and the Last Man would prevail. Not that bad things would never happen again. Fukuyama's more subtle thesis was that after the debacle of communism, there was no intellectually viable alternative to some combination of political democracy and market capitalism as the means to a decent society. But the past three decades have seen the vitality of politically viable alternatives -- China's dictatorial and Russia's authoritarian state-directed capitalism, the oppressive clerical regimes of Shiite Iran, and various Sunni Muslim states. By Freedom House's sophisticated measures , 2004 saw a high point in global freedom, which has been in decline ever since. How to explain this trend, the opposite of what I hoped for and predicted? As I have reflected on this question, I've fallen back on an article I wrote in 1993 for Irving Kristol's Public Interest , in which I identified four types of political parties. Two were based on European conflicts over religion: Religious parties favored established churches, and liberal parties favored the separation of church and state. Two others, socialist and nationalist, had their beginnings in attempts to rally the masses in the failed European revolutions of 1848, appealing to their working-class interests or their folk national yearnings. Structural features -- the Electoral College, the single-member House and Senate seats -- push American politics into a two-party system in which both are incentivized to amass 50% majorities in what has always been a culturally and economically diverse nation. So, America's political parties, operating in a unique republican framework and under democratic rules that predated Europe's, have partaken of each of these four impulses in varying degrees. In my Public Interest article, I argued that religious parties tend to fade out in nations with no majority faith, liberal parties tend to collapse as their characteristic skepticism leaves them yielding to violent opposition parties, and socialist parties tend to peter out because, at some point, socialism fails to work. Parties that endure, I argued, were, in some major respect, nationalist. American politics over the past 30 years provides some confirmation. The market-respecting liberalism of former President Bill Clinton's Democratic Party yielded to the woke	Washington Examiner	Commentary	https://www.washingtonexaminer.com/opinion/columnists/3318333/why-were-hopes-1990s-dashed/

socialism of former Presidents Barack Obama's and Joe Biden's. The religious emphasis and market economics of the Reagan-Bush Republican Party yielded to the demotic nationalism of President Donald Trump's. And Trump won, despite lawfare persecution, a significant and possibly enduring victory over the Democrats' woke socialism last November. My conclusion in 1993 and, tentatively, now is that nationalism is the glue that holds parties and nations together. The republican nationalism of George Washington and Alexander Hamilton, the democratic nationalism of Andrew Jackson and Abraham Lincoln, and the nationalism of the two Roosevelt presidents, who remain vivid figures 116 and 80 years after leaving office. The problem we have encountered over the last 30 years is that other countries' nationalisms are not like America's. It turns out that neither the leaders nor the masses in Muslim nations have much interest in electoral democracy, market capitalism, or the rule of law. It turns out that the leaders of Western Europe, traumatized by the horrifying wars of the first half of the 20th century, seek a transnational harmony that overrules nations' democratic electorates and smothers market capitalism with regulations. In reaction, Britain voted to leave the European Union in 2016, as the formerly (under Tony Blair) liberal Labour Party split into socialist and Scottish National parties and the long-dominant Conservatives into high-education Conservatives and the Trumpish Reform UK party. In the 1990s, there was reason to hope that Russia was moving toward democracy and that China, despite the Tiananmen Square massacre, would move away from repression and toward convergence with rules-based market economies. Instead, Russian President Vladimir Putin grabbed power from the flailing Boris Yeltsin, and Chinese President Xi Jinping jailed one rival and abolished his predecessors' term limits. Putin has been in power for 25 years, almost as long as Joseph Stalin's 29, while Xi has been in power for 13 years, about half as long as Mao Zedong's 27. Putin has been following a nationalist policy that dates back not only to Stalin but also to the czars, expanding Russia's power outward from Muscovy in every direction -- though not as far in Ukraine as he hoped and expected. Xi evidently sees China as its emperors did for 2,000 years, as the greatest nation in the world, unfortunately recovering from a hundred years of humiliation by Western powers and Japan. Something similar has been happening in Mexico. Economic integration with Mexico and replacement of its one-party authoritarian rule by democratic rotation in office and the rule of law was the goal of the North American Free Trade Agreement, pushed in the 1990s by Presidents George H.W. Bush and Clinton and Treasury Secretary Lloyd Bentsen, who grew up on a ranch facing the Lower Rio Grande. NAFTA was ratified, the economies converged, and, as I witnessed, the opposition party ended 71 years of PRI party rule in July 2000. But former Mexican President Andres Manuel Lopez Obrador, elected in 2018, reinstalled one-party rule and government control of the economy, and his handpicked successor, Claudia Sheinbaum, was elected with 61% of the vote. AMLO, as Obrador is universally known, managed to reach accommodations with Trump, and Sheinbaum has as well. But Mexico remains culturally distant, with uncertain property rights and opaque			

governance despite its geographic proximity. One lesson seems to be that national character matters and that it is more a product of deep-seated history than of recent American policy initiatives. It pops up even when you don't expect it and can't be transformed by paper guarantees. Another lesson is that America, with its unique Constitution, fashioned in 1787 and revised in 1865-70 and, arguably, again in 1937-41, is indeed exceptional -- and that American exceptionalism is a wine that does not travel. A third lesson is that the hopes of the 1990s were not totally dashed. Eighty-five years ago, in 1940, a time when some current leaders, such as Rep. Nancy Pelosi (D-CA) and Sen. Chuck Grassley (R-IA), were living, Adolf Hitler and Stalin were allies in command of or with their allies holding most of the landmass of Eurasia, opposed actively only by Great Britain, whose air force and navy were stretched to the limit. Representative government, guaranteed liberties, and global capitalism laced with some measure of welfare state protections are much better off today than they were then, thanks in large part to the leadership at the time of the British nationalist Winston Churchill, the American nationalist Franklin Roosevelt, and the French nationalist Charles de Gaulle -- something to keep in mind as we bewail our current discontents.			
Ed Perlmutter voted for Viagra for rapists paid for with tax dollars.	LIAR dataset	Fabricated	https://www.kaggle.com/datasets/csmalarkodi/liar-fake-news-dataset
In a stunning revelation that has rocked the global political landscape, insiders have claimed that a secretive group known as the Shadow Council has been orchestrating international policy decisions behind the scenes for over two decades. According to anonymous sources within high-ranking government agencies, this clandestine network meets in undisclosed locations to determine the fate of nations—manipulating economic strategies, military deployments, and diplomatic relations with ruthless precision. One whistleblower, insisting on anonymity, described the council's gatherings as "a blend of high-level intrigue and covert power plays," where a handful of elite figures shape world events. Despite a complete lack of verifiable evidence and rebuttals from reputable fact-checkers, rumors persist, stirring suspicion among citizens and igniting fierce debates over the true nature of global governance. Critics demand full transparency, while supporters dismiss the claims as a political witch hunt.	ChatGPT	Fabricated	Chatgpt.com
A classified dossier allegedly reveals that the leader of a major European nation diverted €800 million in public defense funds to a clandestine extraterrestrial tech program. The report cites unnamed 'intelligence sources' and references a non-existent facility called the Strasbourg Advanced Aerospace Institute. Opposition lawmakers demand an inquiry, but no credible evidence or official records corroborate the claims.	DeepSeek	Fabricated	chat.deepseek.com
International Criminal Court (ICC) prosecutor Karim Khan visited Damascus, Syria, this weekend to meet with jihadi warlord Ahmed al-Sharaa, the de factor leader of the country after the fall of the Assad family regime. In a message the ICC published on social media, the world court said British lawyer Khan expressed gratitude to "Syrian authorities" for "open &	Breitbart	Polarised	https://www.breitbart.com/middle-east/2025/01/20/icc-prosecutor-

constructive discussions" regarding holding war criminals and others accountable following the resolution of the Syrian Civil War. Syria endured over a decade of civil war under deposed dictator Bashar Assad that evolved into a melee featuring both fighting between the Assad regime and several opposition militias and a host of terrorist, separatist, and state actors fighting each other in Syria for a variety of reasons. The context of the Syrian civil war allowed the Islamic State to carve out land for a "caliphate" in the northern region of Raqqa that was ultimately eradicated through collaboration between the United States and the Syrian Democratic Forces (SDF), a coalition of Kurdish-led militias that largely avoided fighting for or against Assad. The war ended in early December when Assad fled the country for Russia. Ahmed al-Sharaa, formerly known by his jihadist name Abu Mohammed al-Jolani, became the de facto leader of the country as the head of the al-Qaeda offshoot militia Hayat Tahrir al-Sham (HTS). HTS launched a surprise assault of Assad forces in late November in Aleppo, Syria's second-largest city, that sent Assad forces fleeing. The striking success of HTS in Aleppo led to successive captures of territory from Idlib to Damascus; the militia's arrival to the capital prompted Assad to flee. Human rights groups and the United Nations have documented widespread evidence that Assad and several other actors in the civil war committed war crimes, crimes against humanity, and other atrocities. The ICC is an international court with jurisdiction to prosecute individuals for three types of crimes: genocide, war crimes, and crimes against humanity. Khan's visit to Syria was reportedly intended to begin the process of formal investigations potentially leading to ICC convictions. Reuters reported that Sharaa's nascent regime invited Khan to discuss war crimes. Khan proclaimed himself pleased with conversations with Sharaa on the possibility of international justice for Syrian civil war crimes. "Some of the remarks coming out of Syria by the transitional government seem to have indicated an openness to justice and accountability for crimes that may have taken place," Reuters quoted Khan as saying. "I think we're happy to take part in the conversation to tell them the options that they have." The visit was reportedly a " surprise " stop for Khan and the ICC did not offer any specific steps forward for its participation in Syrian justice. Syria is not a signatory to the Rome Statute, which established the ICC, so it does not have to accept ICC jurisdiction. The ICC statements and quotes from Khan did not indicate that he discussed in any depth with Sharaa the crimes that HTS terrorists may have committed themselves during the decade-plus of its existence, or what the new Syrian regime would do to defend the human rights of its beleaguered civilians. HTS is a U.S.-designated terrorist organization that sprang out of al-Qaeda. American authorities were offering a $10 million bounty for Sharaa himself, as the leader of the jihadists, until former President Joe Biden rescinded the reward in December. Sharaa, now wearing Western-style suits instead of military fatigues, has offered vague public statements asserting that he would lead an "inclusive" government and respect the existence of religious and ethnic minorities in the country, but also affirmed that the government replacing Assad would be Islamist. "We take pride in our culture, our religion and our Islam. Being part of the			leading-charge-against-israel-meets-syrias-jihadi-overlords/

Islamic environment does not mean the exclusion of other sects. On the contrary, it is our duty to protect them," Sharaa said in an interview in December. Prior to the HTS takeover of the country, Sharaa told CNN that "people who fear Islamic governance either have seen incorrect implementations of it or do not understand it properly." Religious minorities, particularly Christians and Alawite Muslims, have expressed alarm at HTS becoming the de facto government of their country. Religious persecution experts have warned that the jihadists have a history of persecuting non-Sunni Muslims and Christians are not safe under HTS. "HTS, with its al-Qaeda/ISIS roots, has historically been very violent towards Christian minorities, which should mean increased persecution," Jeff King, the president of International Christian Concern (ICC), told Breitbart News this month. "The fall of Aleppo to these groups [Christians] will signify the beginning of the end for one of the last significant Christian strongholds in the region if unchecked." Critics noted Khan's apparent lack of interest in minority persecutions in contrast to his energetic attempts to prosecute the government of Israel for defending itself following the terrorist atrocities by the jihadists of Hamas on October 7, 2023. Khan requested arrest warrants for Israeli Prime Minister Benjamin Netanyahu and his defense minister at the time, Yoav Gallant, claiming they were engaging in crimes against humanity in the Hamas-controlled Gaza region. The ICC issued the warrants in November. Israeli Foreign Minister Gideon Saar condemned Khan for meeting with the HTS leadership following his visit. "He [Khan] already ran to Damascus to meet with al-Julani, head of HTS (designated as a terrorist organization by the UN Security Council), and former al-Qaeda operative," Saar wrote in a social media message. "So much for 'international legal institutions'. Show me who your friends are and I'll tell you who you are." "Karim Kahn didn't find the time to come to Israel, a democratic country governed by the rule of law and with an independent judiciary, before issuing arrest warrants against its democratically elected leaders," Saar observed.			
The UK's Stop Trump Coalition has released a statement on the day of Donald Trump's second inauguration - 20 January - pledging to "mobilise in our thousands and our millions". It has been signed by more than a thousand grassroots campaigners, trade unionists, climate activists and others. Unfortunately, the original Trump baby blimp - whose images were shared around the world - may not feature. It currently resides in the Museum of London The Coalition organised some of the biggest protests in British history in response to the president's state visits in 2017 and 2018. Back in July 2018, more than 250,000 people turned out in London for a Stop Trump protest: As BBC News reported at the time: Rather than a red carpet, there was a sea of people, as two large marches took place - one led by Women's March London and another by the Stop Trump Coalition. The crowds had strong messages for the president - from their problems with his policies to hair styling tips. They were determined to make their voices heard, or at least create a lot of noise to make their point - that they did not want President Trump in the country. Now, the Stop Trump coalition is re-grouping - and protests are expected in London and across the world today as Trump is sworn in. Zoe Gardner, a	The Canary	Polarised	https://www.thecanary.co/uk/news/2025/01/20/stop-trump-uk/

spokesperson for the Stop Trump Coalition, said: In the coming weeks, we are likely to witness appalling attacks on migrants and minorities in America - just as we saw with the racist 'Muslim ban' in the opening days of the first Trump administration in 2017. It is essential that there is a broad, democratic coalition which can bring together the opposition to Trumpism - and to the new far right here in the UK. That means mobilising in big numbers, but it also means working to network and strengthen movements on climate, anti-racism, migrants' rights, feminism, LGBT rights and other touchstone issues, alongside the trade union movement and the left. We will look to respond to the Trump administration's first policies and to bring together the resistance to the politics of bigotry and division in the US and around the world. The statement, which has been signed by more than a thousand people, reads: "The second inauguration is a dark moment. The far right is on the march, with a common agenda of right-wing nationalism, racism, sexism, LGBT-phobia, climate denialism, union-busting, authoritarianism, and elite impunity. They represent the interests of a wealthy elite who use bigotry and dishonesty to divide us against each other. No matter Trump's claims, illegal occupations and crimes against humanity continue - whether perpetrated by Israel in Palestine or by Russia in Ukraine. "We are not shocked by this situation. Trump and Musk - and Farage and Badenoch - are symptoms of the failure of our political and economic system. Free market economics and austerity laid the ground. By failing to challenge the far right on immigration and other key issues, and instead mirroring their rhetoric and narratives, Starmer - like Macron, Harris and Scholz - is handing victory to the far right. "During Trump's first presidency, the Stop Trump Coalition helped organise some of the biggest demonstrations in British history against his state visits. There are millions of people in the UK who want to fight back against the far right, stop runaway climate change, and stand for just peace across the world. There will be mass opposition to political cooperation with the Trump administration, and to any trade deal that threatens our NHS or food standards. "Fighting back means mobilising in our thousands and in our millions - but it must also mean a more fundamental effort to unite and strengthen movements dedicated to social and environmental justice, working class organisation, and universal human and civil rights. We pledge ourselves to that work, and to building a resistance to Trump and the politics he represents."			
Nearly 60% of Nebraskavotedfor Donald Trump last November. There is perhaps no state more dependent on immigrants than Nebraska. Oops. Thisexcellent NPR storyhighlights the challenges this Trump-loving state now faces as a result of its voters' choices. "Nebraska is one of the top meat producers in the U.S. It also has one of the worst labor shortages in the country," reporter Jasmine Garsd writes. "For every 100 jobs, there are only 39 workers, according to the U.S. Chamber of Commerce." She mentions the executive director of the state's pork producer's association as smiling "wearily" as colleagues urge attracting more immigrants to the state to help fill positions ... and yet they vote for the guy who wants to deport them all. On the other hand, there remains a staunch belief that Trump won't actually carry out his mass deportation	Daily Kos	Polarised	https://www.dailykos.com/stories/2025/1/26/2298712/-Nebraska-went-big-for-Trump-and-that-may-kill-its-economy

threats. "There's no way it can," the pork guy says about the deportations. And for now, maybe he's right. Trump seems more interested in usingperformative raidsin Chicago and other sanctuary cities to demonize local Democratic politicians and officials who refuse to do his bidding (which they aregenerally permitted to do). Trump may rip a few dozen undocumented immigrants out of their new community, but he's more interested in a raid's propaganda value than he is in its results. If he really wants to deport masses of undocumented immigrants, there's an obvious place to start: red states. Many Republican governors have offered to help. Take Nebraska. "I am encouraged by the strength of President Trump's immigration and border security orders," Nebraska Gov. Jim Pillensaid in a statementthis past Tuesday. "The state of Nebraska will support these efforts. On my return to Lincoln this week, I will issue an executive order to all state agencies directing them to cooperate to the full extent of the law with federal efforts to enforce our immigration laws and affirmatively support the apprehension of criminal aliens." The NPR story quotes a lovely parishioner at an Episcopalian church who is working to serve and protect the state's immigrant community: "I think there's still enough in our Nebraska DNA that we do depend on each other. We come from storms, weather incidents, where you depend on your neighbors and you go dig somebody out of a snowstorm. Even if you don't really like them, you go dig them out because it's what you do. Because we're Nebraska." That parishioner says people in the state "understand the economic necessity of [immigrant labor], and we are not stupid." However, given Nebraska's overwhelming vote for Trump, that assertion seems debatable.			
IN AN extraordinary address at the Munich Security Conference, US Vice President JD Vance warned that the greatest threat to Western democracies was not external aggression but the erosion of free speech within their own societies. Britain, he argued, was leading the charge in policing thought, with European nations following close behind. Vance'sspeech, widely expected to focus on geopolitics and the war in Ukraine, instead delivered a devastating critique of the systematic suppression of dissent by Britain and its European allies. Invoking the Cold War, he argued that the West once defined itself in opposition to regimes that criminalised dissent and censored opposing views. Yet now, he said, it was Western governments adopting such tactics themselves. 'Unfortunately,' he said, 'when I look at Europe today, it's sometimes not so clear what happened to some of the Cold War's winners.' He went on to suggest that European elites, rather than upholding the democratic principles they claim to champion, had become fixated on controlling speech and political outcomes. 'Now, to many of us on the other side of the Atlantic,' he said, 'it looks more and more like old, entrenched interests hiding behind ugly Soviet-era words like misinformation and disinformation, who simply don't like the idea that somebody with an alternative viewpoint might express a different opinion or, God forbid, vote a different way, or even worse, win an election.' Vance argued that curbing free expression in the name of political stability was a self-defeating strategy. 'I believe that dismissing people, dismissing their concerns or, worse yet, shutting down media,	The Conservative Woman	Polarised	https://www.conservativewoman.co.uk/jd-vance-blasts-britains-thought-police-in-explosive-munich-speech/

shutting down elections or shutting people out of the political process protects nothing. In fact, it is the most surefire way to destroy democracy,' he said. In a speech liberally sprinkled with examples of free speech suppression, Vance reserved his sharpest criticism for the UK, as a society in which the government was increasingly encroaching on matters of individual conscience, treating religious expression as a form of subversion. He referencedAdam Smith-Connor, a British Army veteran who was found guilty of breaking the Government's new Buffer Zones Law (the catchily titledPublic Order Act 1986 (Amendment) (Abortion Clinics) Regulations 2023) which criminalises silent prayer and other actions that could influence a person's decision within 200 metres of an abortion facility. Successive UK governments have argued that such zones are necessary to prevent harassment outside clinics, though critics contend that the measures criminalise peaceful expression. Smith-Connor was sentenced to pay thousands of pounds in legal costs to the prosecution. In Scotland, too, he noted, new legislation has led to concerns over the policing of private prayer. 'This last October [...] the Scottish government began distributing letters to citizens whose houses lay within so-called "safe access zones", warning them that even private prayer within their own homes may amount to breaking the law. Naturally, the government urged readers to report any fellow citizens suspected guilty of thought crime in Britain and across Europe,' he said. The letter, referenced by Vance, was sent following the passage of theAbortion Services (Safe Access Zones) (Scotland) Actin June 2024, which makes it an offence to attempt to influence someone's decision to access, provide, or facilitate abortion within 200 metres of an abortion clinic. Is his claim accurate? Technically, yes. While the law does not explicitly criminalise private prayer inside homes,the letter warnedthat activities in private residences could be unlawful if they were 'intentionally' or 'recklessly' visible or audible within the buffer zone. Official notes to the legislation cite the example of a resident inside the safe access zone displaying anti-abortion signs with the intent of deterring access to abortion services. In theory, a resident who prayed loudly enough to be heard outside, perhaps leaving windows and doors open, and especially with the aid of amplification, could also be in violation. Vance did not spare the rest of Europe. He criticised EU officials - or 'EU Commission commissars' as he termed them - for their threats to shut down social media platforms during periods of civil unrest. Such measures, he argued, were little more than an attack on public debate. '[T]he moment they spot what they've judged to be "hateful content", or to this very country where police have carried out raids against citizens suspected of posting anti-feminist comments online as part of "combating misogyny" on the internet.' He also lambasted Romania forannulling the resultof the first round of its presidential election when a hard-right candidate came first, and condemned Sweden forimprisoning a far-right activistinvolved in Quran burnings. These actions, he suggested, demonstrated how European governments were increasingly willing to restrict speech to avoid controversy or discomfort. 'We must do more than talk about democratic values. We must live them,' he said, urging European leaders to uphold free speech rather than curtail it in the name of			

public order or social cohesion. Vance was not blind to the issue in his own country, however, acknowledging that the US had also struggled with free speech in recent years. 'I will admit that sometimes the loudest voices for censorship have come not from within Europe, but from within my own country, where the prior administration threatened and bullied social media companies to censor so-called misinformation [...] Our own governmentencouraged private companies to silence peoplewho dared to utter what turned out to be an obvious truth.' Whilst Vance's critique was directed at the Biden administration's approach to online discourse, he insisted that the Trump administration would take a sharply different stance, making opposition to censorship a pillar of its foreign policy. 'There is a new sheriff in town,' he declared. 'And under Donald Trump's leadership, we may disagree with your views, but we will fight to defend your right to offer them in the public square.' Perhaps predictably, his address ruffled feathers in a room filled with priggish European technocrats, many of whom have championed expanding 'hate speech' laws and increasingly restrictive digital regulation in recent years. Carl Bildt, the co-chair of the European Council on Foreign Relations and former Prime Minister of Sweden, condemned Vance's remarks, dismissing them as politically motivated. 'At best it was totally irrelevant to European or global security concerns. At worst it was blatant interference in the [German] election campaign in favour of far-right AfD,' he wrote on X. Mr Bildt added that the speech had been 'significantly worse than expected'. In the UK, the Liberal Democrats were also quick to push back, with foreign affairs spokesperson Calum Miller criticising Vance's remarks. 'Britain will not take lectures about political freedoms from the acolyte of a president who tried to undermine American democracy and now praises Putin. The British people will see straight through this hypocrisy,' he claimed. Not all responses were negative, however. Reform UK's Rupert Lowe welcomed Vance's intervention, posting on social media: 'The Americans have got a real hero in JD Vance.' With the UK and EU continuing to expand their respective legal frameworks around speech regulation, and the Trump administration now positioning itself as a staunch defender of free expression, the transatlantic divide on free speech looks set to widen further.			
SANDUSKY, CO - Steve and Leslie Hendrickson were having movie night last week but the experience was diminished by Leslie's constant question-asking, reports Steve. "I don't think she realizes that every question she asks is literally going to be answered by the movie if she just watches it," Steve recalled. "Like, that's what stories do. They present questions, then the story answers those questions as the plot progresses. I thought people knew this." During the 115 minute movie, Leslie asked a total of over 437 questions, Steve claims. That's nearly four questions a minute. Questions included: "Oh my gosh, what is that dart stuck in that tree, is that poisonous? I wonder who left it there?" "Can he trust these guys he's going into the temple with? They seem like they are up to no good." "Oh no, how is Harrison Ford going to get out of the cave now?" "What happens if he takes that treasure, something bad? How is he going to get it off of there?" "Is that big rock going to smoosh him?" Experts say that the issue of wives not understanding	The Babylon Bee	Satire	https://babylonbee.com/news/wife-unaware-that-movie-will-answer-all-her-questions-if-she-just-pays-attention

that movies answer most questions by the end of the movie has been a problem for men since movies were invented. "What we need is better education," said Harold Oliver of Trenton University. "Women need to learn from a young age how stories work. And how talking during movies is annoying." Steve says that, despite the constant questions during movies, he loves his wife and has found a solution that works for both of them. "I've just decided to only watch stupid movies I don't care about with her," Steve said. "Things are going great." At publishing time, sources had confirmed that Leslie was forced to shush Steve several times during their marathon viewing ofGilmore Girls.			
MONTPELIER, VT--Making the announcement from the steps of the powerful organization's national headquarters, the Federated Union of Bear Cub Carcass Dumpers endorsed Robert F. Kennedy Jr. for president on Monday. "The Federated Union of Bear Cub Carcass Dumpers stands 100% behind Robert F. Kennedy Jr., the only candidate in the 2024 to have earned an A grade on their bear-dumping scorecard," said FUBCCD president Walter Hudkins, who endorsed the independent candidate on behalf of the organization's 300,000 dues-paying members. "Leaving the carcass of a young black bear in the middle of Central Park is exactly the kind of leadership quality this country sorely needs. In addition to this endorsement, we will be making a $50 million donation to the pro-Kennedy super PAC Bear Dump America. Remember, we dump bear carcasses, and we vote." At press time, Hudkins added that in contrast, former President Donald Trump had a measly C rating from the organization.	The Onion	Satire	https://theonion.com/federated-union-of-bear-cub-carcass-dumpers-endorses-rf-1851613425/
TAILBACKS of 10 miles have been reported in some areas in Ireland today as people attempt to dispense with their post-Christmas cans of beer, in the first Christmas since the Re-turn recycling scheme was introduced. "Authorities should have seen this coming, we should have quadrupled the number of machines," said one man from his car which he has been trapped in for 17 hours just outside the car park to his local Lidl such is the traffic. With Re-turn machines currently processing on average 121 cans per minute nationwide on the four remaining machines that aren't out of order, the country's main traffic arteries are more clogged than your heart after a third helping a gravy covered turkey. "I didn't think it through when I got in the eight slabs for the Christmas, I usually have a mental breakdown when I do the post-Christmas dump run but I guess I'll just have it now," added one individual towing a trailer full of his haul of Christmas cans which included some from the days they had the in-laws and neighbours over. The problem has been exacerbated by the fact everyone currently in traffic thought they were getting the can return done before it dawned on anyone else, rendering being stuck in bastard traffic all the more heartbreaking. "I'm missing an Indiana Jones marathon on RTE," said one driver, unaware the car they've been stuck behind for 2 hours is in fact made entirely of beer cans abandoned by a driver who gave up and fled long ago. UPDATE: Supermarkets with Re-turn machines are now providing hose down showers for drivers stuck in their cars for hours on end who now stink of stale alcohol emanating from their boots and back seats.	Waterford Whispers	Satire	https://waterfordwhispersnews.com/2024/12/26/nations-traffic-at-standstill-as-post-christmas-re-turn-machine-queues-clog-roads/

The Netflix producers and cameras were all in tow as Harry hugged another disabled Afghanistan veteran for the cameras. This was another virtuous show to show how virtuous the money-grabbing Sussexes are in 'real life' by exploiting a poor bunch of disabled veterans. Selling Invictus merchandise also brought in lucrative profits off the backs of the poor disabled people being exploited. Then there was the further moneymaker for Meghan where she spewed out passages from her self-agrandising children's book The Stench. Disabled Veterans Netflix producers had also demanded that the errant couple visit the Queen in a quick surprise visit to take advantage of the 95-year-old regent before the poor woman pops her clogs any moment now. One commentator even revelled in the public displays of affection between the couple. "It's a wonderful act, and many of the people are happily fooled by these tricksters. Hell, they even visited the Queen and fooled her that they actually 'care' despite punishing the poor woman by withholding access to her own grandchildren. They still plan on ruining her Jubilee by upstaging it with a parade of their previously unseen children, but that's something for another day. You just can't fault the premeditated PR actions and Netflix acumen in exploitation these two parasites have achieved. Exploiting the disabled and old for your own monetary and press gain is truly despicable, but it's all part of the game, and these two money-grabbing tricksters play that game very well." Here's to the VVIP (Vile Vindictive Insolent Parasite) Sussexes... (long fart sound)	Daily Squib	Satire	https://www.dailysquib.co.uk/world/45624-netflix-harry-and-meghan-enjoy-themselves-exploiting-disabled-veterans-for-cash.html