**Utilising Natural Language Processing Models and Visualisations to Identify Bias Within News**

Table of Contents

[Introduction 1](#_Toc161409104)

[Motivation 1](#_Toc161409105)

[Contributions 2](#_Toc161409106)

[Objectives 2](#_Toc161409107)

[Background 3](#_Toc161409108)

[What is bias? 3](#_Toc161409109)

[How is bias demonstrated in text 3](#_Toc161409110)

[Effects of bias 4](#_Toc161409111)

[Bias in news reporting 4](#_Toc161409112)

[Current technologies and related works 5](#_Toc161409113)

[Hugging face 5](#_Toc161409114)

[Large language models 5](#_Toc161409115)

[LLM chatbots (Chat GPT/GEMINI) 6](#_Toc161409116)

[Utilising the API for Bias Detection 7](#_Toc161409117)

[Topic based sentiment analysis. 7](#_Toc161409118)

[Sentiment analysis 7](#_Toc161409119)

[Topic based sentiment analysis(TBSA). 7](#_Toc161409120)

[Application of TBSA 8](#_Toc161409121)

[News Bias Group 8](#_Toc161409122)

[Design and plan of evaluations. 9](#_Toc161409123)

[Dataset and data handling 9](#_Toc161409124)

[Where data is coming from 10](#_Toc161409125)

[Standard practices/plan for evaluations 11](#_Toc161409126)

[LLMs/Chatbots 11](#_Toc161409127)

[Hugging face models 11](#_Toc161409128)

[Works Cited 11](#_Toc161409129)

# Introduction

In this project I aim to utilise existing models and NLP (Natural languages processing) techniques to develop a model of which will accurately identify and understand bias with news articles.

This project will be focused on text-based news, specifically news articles, blog posts and reports of a similar structure.

## Motivation

An Ofcom study in 2023 found that 96% of adults in the UK consume news in some form, with TV accounting for 70% of that number (Ofcom, 2023). Since 2018 there has been a growth of 8% from 22% to 30% in the number of people using social media as their primary form of news, while there has been a drop of 10% of people using direct access to news websites (Newman, 2023). Social media typically has a far more relaxed approach to news of which is likely to be a reason for its recent growth. For example, on TikTok the most followed official news account is Daily Mail at 6,700,000 (As of writing this) (Torbitt, 2024) whereas a comparison the account [@dylan.page](https://www.tiktok.com/@dylan.page?lang=en) has 10.5m followers.

The daily mail account typically follows a similar format to their television news broadcasts, in contrast to the account run by Dylan page of which is far more informal/relaxed. While @dylan.page is a widely respected account known for accurately reporting stories, Due to the nature of social media it gives the option for anyone to post similar videos of which are affective heavily by their views/opinions thus giving the consumer a far more biased account of the stories.

As previously mentioned it is primarily the younger age range of news consumers using social media as a primary source. Due to the nature of the young mind learning quickly it means they are far more impressionable and at risk to this heavily biased content.

I believe that using a pre ladled dataset of news articles and their biases it is possible to build a model of which will be able to identify biases text and give an insight to consumers on the content they are reading.

## Contributions

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## Objectives

The primary objective of this project is to utilise a range of NLP techniques and pre-existing models to develop a comprehensive model for identifying bias within text (in this case news articles). The specific objectives are as follows:

* Produce a comprehensive and ladled dataset containing a range of articles from various news outlets.
* Build and analyse an initial model to gain an insight into performance and how various NLP processes can be utilised.
* Using the data collected in the previous objective, improvements will be planed, tested, and implemented into an improved model.
* Using data collected and visualisations I will evaluate the performance of the model in various cases (e.g. identifying different types of bias)
* Upon completion of analysis and development the report will outline how the differences in the two models affected performance as well as looking at how further improvements could be made in terms of increasing accuracy, speed, and applications.

# Background

## What is bias?

Bias is an inherent aspect of human cognition and interaction. It refers to the predispositions or leanings, often subconscious, that shape our understanding, actions, and decisions. While commonly discussed in the context of news and media, bias extends far beyond influencing a wide range of areas including workplace environments, day to day life, and academic research. Recognising and understanding the various forms of bias is crucial for informed and rational decision making in all contexts (Psycology Today, NA).

Cognitive biases are ranging and can have varying impacts. For instance, confirmation bias describes the brain’s tendency to seek and focus on information that supports existing beliefs, while ignoring opposing evidence. This can lead to a skewed understanding of events or issues (Psycology Today, NA). Another example is the fundamental attribution error, where individuals are prone to attribute someone else’s actions to their personally trains, rather than considering situational factors of which may influence their behaviour (Psycology Today, NA).

These biases can be useful in some instances since they can speed up decision-making by simplifying complex information. However, they can also cause mistakes in judgement and perpetuate prejudices or unjust practices. Being conscious of and actively dealing with these biases is essential for making fair and accurate decisions.

In conclusion, understanding bias is important in many areas since it influences human behaviour as well as societal standards. A thorough examination of the many types of biases and their effects is critical for improving justice, accuracy, and inclusion in decision-making and social interactions.

## How is bias demonstrated in text

Bias in text, whether in news articles, academic writing or in everyday communication can appear in a range of subtle forms. Understanding these manifestations is key to recognising and analysing biased content. Some examples of how bias may be demonstrated are as follows:

1. Word choice and tone: The words and tone used tend to influence the readers perception of an issue. For example, using emotionally loaded words such as referring to a protest as a riot will sway a reader’s perception.
2. Framing of information: The way in which information is presented or framed can often reveal bias. This includes what the author has chosen to emphasize or downplay. E.g. focusing on certain aspects of a story while omitting other parts can create ill adequately informed consumers of which may become biased.
3. Source selection: An author may intentionally/unintentionally select sources in which predominantly reinforce their own opinion. This can lead to the author not becoming aware of counterarguments or perspectives other than their own.
4. Perspective and focus: The perspective from which a text is written may also introduce bias. For instance, writing about topics from a purely western perspective on a global issue may lead to a skewed representation of all facts and can overlook complexities and viewpoints of other cultures.
5. Use of propaganda Techniques: Deliberate use of propaganda techniques such as intentionally using a combination of the pre explained examples is a very clear demonstration of bias in text.

By being aware of the methods in which bias can be demonstrated, readers can develop a more critical eye when consuming inflation. This awareness is crucial for discerning the reliability and fairness of the information they are presented with, and once achieved will allow for a more informed and balanced understanding of the world.

## Effects of bias

Given its impact within society, public perception and political processes, the impacts of media bias are an important worry in today's culture. Academic OUP (oxford university press) research shows how biased news may impact public views, through frequently instilling irrational worries that contradict objective world trends news coverage often leads to a ‘mean world syndrome’. The mainstream media's tendency to exaggerate negative events can create a sense of fear and insecurity among their consumers (Oxford University Press, 2022).

In addition to create a sense of fear and insecurity, media bias also plays a pivotal role in shaping political opinions and behaviours. News outlets with a specific political leaning often influence their audiences’ views, pushing the consumer towards a particular end of the political spectrum. The influence of this bias is especial prevalent within media echo chambers (An echo chamber is an environment where a person only encounters information or opinions that reflect and reinforce their own. (CGF GLOBAL, NA).

Furthermore, the perception of media bias significantly impacts public trust in the respective outlets. A report by Gallup suggests that most Americans acknowledge the critical role of media in democracy however “More than eight in 10 Americans say the media bears "a great deal" (47%) or "a moderate amount" (36%) of blame for political division in this country.” (Gallup Inc, 2020).

In conclusion, media bias impacts society in important ways. It shapes how people view the world and influences their political beliefs. When the media portrays events with a certain slant, it can create a biased understanding of reality. This leads to a decline in trust towards these media sources. As trust diminishes, societal divisions deepen, making constructive conversations more challenging and hindering effective public dialogue. Ultimately, this can weaken the foundations of democracy, which relies on a well-informed public making decisions based on unbiased, accurate information. Thus, recognizing and addressing media bias is crucial for maintaining a healthy, democratic society.

Top of Form

Bottom of Form

## Bias in news reporting

Bias in news reporting is a significant issue that impact how audiences perceive and understand the news. News organisations and journalists strive to adhere to a code of ethics to ensure fair and reliable reporting, but biases can still appear in a variety of ways. These biases may not only arise in the interpretation/presentation of facts but also in the secretion of stories and sources. For example, the decision for what stories to cover, the sources used and how the information is displayed to the consumer may all reflect a particular bias.

An important aspect of understanding media bias is recognising the distinction between news gathering and news analysis. News gathering involved investigative word and fact-checking, while news analysis interprets the facts within a larger narrative. Newspapers such as The NY Times and the Wall Street journal engage in both activities. The bias often noticed in such outlets primarily pertains to the news analysis segment, influencing what they chose to cover and how they arrange the collected facts (Engle, 2024).

Racial bias in media reporting has also been well documented. Studies have shown that minorities are more often portrayed negatively in the news in comparison to others. This has been seen to influence public perception and thus societal attitudes. An example of this is to look at police stories where: African Americans have been overrepresented as perpetrators in crime news, whereas whites have been overrepresented as police staff (Wihbey, 2015).

The way media presents different stories may suggest various biases. For example, a heavy reliance on police enforcement narratives in reporting may unintentionally develop prejudices against specific communities. In foreign policy reporting, there may be an implicit assumption regarding the legitimacy of a country's aims, which may not always be supported by documented facts (FAIR, 2012).

Overall, bias in news is a complex issue of which requires very careful consideration and critical analysis by its consumers. By being aware of different forms of bias and understanding the distinction between accurate/factual reporting and analysis, readers can better navigate the range of media sources and gain a more balanced and informed perspective of different stories. Recognising the inherent biases in all forms of media, is crucial for a more comprehensive understanding of the news (Memmott, 2023) (Mastrine, 2022).

# Current technologies and related works

## Hugging face

## Large language models

Large language models, such as GPT-4 and BERT, represent a significant advancement in the field of AI and NLP. These models are built upon deep learning techniques and are trained on vast amounts of text data.

The primary function of LLMs is to understand, generate and manipulate human language in a way that is understandable and accurate to the use case they can complete a wide range of tasks such as translating and summarising test. Along with answering questions and writing code.

While they are not specifically designed for the purpose. Due to the nature of the systems, they can be utilised for the detection and analysis of text. Bias can appear in a wide range of forms, e.g. gender, racial or cultural bias, and can be both explicit and implicit. As these models are trained on such vast quantities of data it means that they can potentially be better equipped for understanding a wider range of biases than say a model trained to find political bias. Being tasked on understanding racial bias.

Differently to other methods such as sentiment analysis there is a far longer process for using LLMs in this case. They are often found as follows:

1. Data Analysis: LLMs can process extensive amounts of text to identify potentially biased language. This can include analysing word associations, sentence structure and the context of specific terms/phrases used.
2. Pattern Recognition: Through their training, LLMs learn to recognise patterns in language. This capability can be utilised to identify recuring themes of which may suggest the appearance of bias.
3. Contextual Understanding: One key strength of LLMs is their ability to understand context. This is crucial in bias detection, as the context in which words are used can significantly alter their meaning and thus perception.
4. Comparative Analysis: LLMs can compare different text sources or segments within the same entity to identify differences of which may indicate bias. For example, an LLM could be used to understand the description of similar achievements by different groups of people.
5. LLMs such as GPT-4 also have feedback implemented, be it just a thumbs up or down, asking the user to pick between two options for answers allows these models to grown in confidence as well as accuracy in their answers are they are used more and more.

There is however one large risk with LLMs, that being that they themselves are subjectable to bias. All models run the risk of being biased through potentially being trained with biased/inaccurately labelled data. With LLMs this isn’t typically a huge issue as they are often trained on data sources from ranging curators whereas smaller niche models may be more impacted. However, many of the “chatbots” such as GPT-4 can also learn of the prompts given to it by the users therefore if they are consistently fed biased information, they themselves can be come biased.

### LLM chatbots (Chat GPT/GEMINI)

LLM chatbots such as Chat GPT and GEMINI are not designed for media bias detection however their ranging capabilities in language understanding make them a useful assistance tool for bias detection. There are a range of ways in which they can be applied for bias detection, such as:

1. Content and Context analysis: These models can analyse news content, tone and framing of ideas. This analysis helps with identifying biases that may influence the readers perception of the stories.
2. Comparative Text Analysis: Through comparing the coverage of similar news events from several different sources, these models can highlight key differences in reporting. While this doesn’t explicitly find bias it can be used as an indicator for where bias may lurk.
3. Pattern Recognition in Language Use: LLMs advanced pattern recognition abilities allow for them to detect recurring biased language patterns within articles, offering insights into frequent biases from specific outlets or journalists.
4. Interactive Learning from Feedback: As both models can incorporate user feedback into their learning processes, it means they can improve their ability to detect biases as they are used more and more. For example, if users consistently point out certain bias in text where the LLM struggles it will become better and identifying said bias.

These chatbots not only display an advancement in current technology but also as an insight to where AI for processed such as bias detection may lead. These models offer a fast and in-depth analysis approach to understanding biases. However, it’s crucial to acknowledge that while these AI tools are powerful, they are specifically designed for bias detection and should thus be used in conjunction with other related tools to ensure the best results.

### Utilising the API for Bias Detection

The APIs of Chat GPT and GEMINI are key tools in automating bias detection in news articles. Through the utilization of these APIS it allows for a more streamlined analysis and processing of the large text coming from news articles. The key features include:

* Automated Text Processing: The APIs enable rapid processing of text, allowing for quick analysis of numerous articles for bias indicators.
* Customizable Analysis Parameters: Users can tailor the APIs to focus on specific types of bias, such as political or cultural, enhancing the relevance and precision of the analysis.
* Real-Time Analysis: The APIs ability to be called automatically allows for real time processing of any new articles.
* Scalability: The APIs can handle varying scales of data, from analysing a single article to processing thousands, making them suitable for both small-scale and large-scale media analysis projects.

While not all these benefits are hugely beneficial in all cases, e.g. the real-time analysis in the case of this project, it is impotent to recognise the potential applications. Using these APIs offers a powerful and efficient approach to identifying and understanding biases in news reporting, contributing significantly to the fields of journalism, media studies, and public discourse.

## Topic based sentiment analysis.

### Sentiment analysis

Sentiment analysis (also known as opinion mining) is a subsection of NLP that focuses on identifying and categorizing opinions expressed in text. The -standard goal is to determine the texts attitude with regards to a specific topic or in general for the document. This process involves analysis textual elements to understand weather the opinions are positive, negative, or neutral.

The outcome of sentiment analysis is typically represented with a numerical scale. This scale often ranges from -1 to 1, where the negative score indicated a negative sentiment. This quantification of text allows for a quick understanding and can be leveraged for further insights in conjunction with other tools.

There are two primary approaches for sentiment analysis. Lexicon-based methods involve utilising a pre-defined list of words and phrases with assigned sentiment values. The sentiment of a text is then calculated based on the cumulative scores. The other option is utilising ML, ML techniques involve training an algorithm (such as Naïve Bayes or deep learning models) on a large dataset of labelled sentiment data. The model learns to classify the sentiment based on the features extracted from text.

### Topic based sentiment analysis(TBSA).

Topic based sentiment analysis represents a refined approach within the field of sentiment analysis. Differing from traditional methods that asses the overall sentiment of a document, this technique focuses on extracting and analysis sentiments related to specific topics within the text.

There are two key “steps” when performing TBSA. The first of which is to identify the topics present within the text. This is typically accomplished using algorithms such as Latent Dirichlet Allocation (LDA) and Non-negative Matrix Functions (NMF) or through utilising deep learning models trained for identifying topics. For example, LDA identifies hidden structures in text collections by grouping words that often appear together into topics,

The second stage for TBSA is performing sentiment analysis on the segments on texts responding to each of the topics. This approach provides a detailed understanding of sentiments, assessing the emotional tone related to each specific topic. This differs from general sentiment analysis which offers a boarder, less specific sentiment overview.

While this method enhances the specificity and relevance of sentiment analysis, it also can introduce many challenges. Due to the extra steps needed for accurately identifying topics addressing the variations in sentiment it can lead to inaccuracies and potentially less insight than the standard sentiment analysis processes outline previously.

### Application of TBSA

A primary application of TSBA in bias detection is its use in comparative analysis. This involves assessing sentiments regarding the same topics across various sources or over different time periods. For instance, by comparing the sentiment towards a political issue in different news outlets, TSBA can highlight inconsistencies or leanings that might indicate a bias. Similarly, observing how sentiments about a topic have shifted over time can uncover evolving biases, reflective of changing societal or media perspectives.

Another significant application is the multidimensional sentiment analysis capability of TSBA. It goes beyond mere positive or negative sentiment evaluation, delving into the intensity and subjectivity of emotions associated with specific topics. This aspect is crucial in detecting biases, as disproportionate emotional responses, or high levels of subjectivity in texts about certain topics can be indicative of an underlying bias.

TSBAs effectiveness for bias detection is also apparent with its integration with other analytical techniques. For example, combining TSBA with fact-checking tools can reveal weather sentiments align with factual accuracies or inaccuracies, this further indicates potential biases within the information. An alternative is merging TSBA with social network analysis. This can help in understanding how sentiments and biases spread through social networks, allowing for insights into both the reach and thus the influence/effect of these biases.

In summary, Topic-Based Sentiment Analysis (TSBA) is adept at revealing hidden biases through comparative and multidimensional sentiment analysis, of which make it a crucial tool in bias detection. Its integration with other analytical techniques such as fact-checking and social network analysis further enhances its ability to identify and understand biases in information.

## News Bias Group

The Media Bias Group is a network of researchers focused on researching media bias from various perspectives including but not limited to computer science, economics, and politics. As an organisation they aim to understand how media bias is perceived, represented, and influences decision-making. Their research spans many fields but includes developing methodologies for creating comprehensive data sets on media bias, automated detection of biased language. Additionally, to this they have studies on the role of linguistic features in media bias and work on creating visualisations to represent media bias effectively.

The organisation is very present on the hugging face platform. Offering a range of public datasets and models of which can be used for both independent and collaborative research. The datasets are diverse and serve a range of purposes in the study and analysis of media content. For the case of this project, I have been primarily looking at “BABE” and “BABE -v3” (with “BABE -v3” being a larger version using data from other projects). I will elaborate further on the datasets in later section of the project.

While the datasets provide much use for researchers the most beneficial work done by the group comes with their models. The models developed by the Media Bias Group are primarily focused on analysing and detecting bias in media content. These models are based on advanced machine learning and NLP techniques, Particular there is a focus on the BERT framework and its variants such as RoBERTa.

* Bias Detection: Many of the models are designed to detect bias in media. This includes identifying political biases, detecting loaded language, and recognising subtle forms of which may not be obvious. The models can analysis text to identify specific words, phrases and/or paters that are indicative of potential bias.
* Text Classification: text classification is a common application within the models. They can categorize text. They care used to group text into various classifications based on the presence or type of bias. For example their “RoBERTa” model is used to return a percentage of text which is deemed to be bias or neutral.

The uses for the models reach far further than the two examples outlined, such as their uses in language understanding and adaptions for further research and analysis.

# Design and plan of evaluations.

## Dataset and data handling

The technological components of the project have been developed utilising a series of Jupyter notebooks. The choice to do so is based on the unique advantages provided by Jupyter's coding environment, the likes of which distinguishes it from traditional Python file formats typically found in editors such as VS Code. One of the key elements of Jupyter notebooks is its cell structure. These cells can execute a variety of functions, including data visualisation, testing, and storage.

The functionality of a cell-based structure can be hugely beneficial in development. It allows rapid experimentation and alterations of small code segments without having to execute larger time-consuming elements of the programme. This functionality is especially useful for visualisations, as Jupyter displays graphs and other visual representations into the notebook itself. This integrated tool speeds up both the code review processes but also allows for easier understanding of any users of the notebook.

Furthermore, developers may use its markdown cell structure to create comments and add further insights to the code. This feature promotes a better understanding and improves communication among team members.. This comprehensive approach guarantees that any person can understand the reasoning behind and contribute effectively to work and decisions on the project.

For the project I have decided to use CSV files for my data storage, this is primarily due to their ease of use and thus suitability for the project at its current scale. As the datasets are relatively small (around 4k rows as largest), CSV files are the most practical choice as they are lightweight and have minimal need for configuration and management in comparison to databases. While tools such as databases or excel files could be implemented at this time their typical advantages are not as relevant in this case, so they have been decided against. However, excel may be used for some processing and visualising in the later stages of the project.

Additionally, CSV files integrate seamlessly with many of python’s data analysis libraries such as pandas. Acknowledging that calling a csv file every time data is needed would be highly impractical I will be using data frames at runtime. Their implementation will allow for quick updates, manipulation, and analysis of which is crucial for the project. Overall, the decision to utilise CSV files in this case lies in their balance of simplicity, functionality, and the requirements of the project.

One important not with the data storage is that with potential further work on the project such as using the models and tools discussed/researched to build and application or website for users to analyse their own own text. A database would need to be implemented.

## Where data is coming from

The data required for this project has been split into two primary categories. These being data collected from hugging face and a group of external sources. The reasoning for these two groups is due to the hugging face having labelled data (either bias labels or other relevant labels) and the extra sources simply holding news article content.

I will be using the BABE-V3 dataset found on hugging face for the vast portion of my project. This dataset has been curated by the previously mentioned news bias group, it is an improved dataset of the original BABE dataset and has been used to train several of their models. This data set has been selected due its similar structure to what is required for the project and will need minimal alterations for my purposes.

The second group primarily encapsulates Kaggle datasets as well as the “NEWS API” API. These are being utilised to cover areas in which the hugging face datasets lack information. For example, the BABE-V3 dataset only has data trained on sentences extracted from news articles and holds no full articles. While that isn’t a huge issue for the training of models it doesn’t transfer perfectly for creating visualisations and tools for understanding larger sets of text. The primary downside of these data options is their lack of any labelling of either biased words or bias for the text. Because of this issue, any analysis created with this data will be qualitative and will utilise visualisations as an assistance tool for manually identifying bias in the text. Alternatively, by employing resources on hugging face or utilizing LLMS such as GPT-4 I can create a labelled data set of which can be used for further testing. I acknowledge that a GPT labelled dataset may not be as accurate as a manually labelled set however it appears to be the only option and will be considered when measuring success with its related results.

## Standard practices/plan for evaluations

To keep the assessments fair, I will be using a standardised method for the evaluation of various models. Using the previously mentioned BABE-V3 dataset I will create a train and test dataset. I am using the 80/20 split for train/test and this dataset will be created through a python script randomly assigning items into each of the datasets. Once this standardised test set is created it will be used for all assessments where it is relevant. By keeping the testing set standardized it ensures a fair evaluation of each of the models.

For any pretrained models they will be assessed with as pretrained models, this will be a baseline for how well they can process data having been trained on a dataset especially made for its purpose. For the evaluation of the models, they will be tested using my testing section from the BABE-V3 dataset. Alongside this plan, where appropriate I will be fine tuning models on my training dataset to create another comparison between the various models. While the first test looks at different training but the same test set, this secondary assessment will evaluate how these models perform when trained and tested on equal data.

There will be a range of tests performed following the explained plan for example using a translation API/LLM I will translate my train/test data to see how these models perform when tasked on a slightly alternative assement.

### LLMs/Chatbots

* Utilising the GPT-4 API
* Can I give it some of my training data and evaluate how well it succeeds on estimating?
* Create some visualisations to show results and findings.

### Hugging face models

* BABE/BABE -v3
  + Doesn’t hold full articles but can test on how my models perform on individual sentences and then look to explore how they perform when adapted to fit larger articles with multiple sentences.
* Discus the transformers python module
* Datasets module
* How they will be evaluated

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